

Power Systems

David Borge-Diez
Enrique Rosales-Asensio *Editors*

Energy System Resilience and Distributed Generation

 Springer

Power Systems

Electrical power has been the technological foundation of industrial societies for many years. Although the systems designed to provide and apply electrical energy have reached a high degree of maturity, unforeseen problems are constantly encountered, necessitating the design of more efficient and reliable systems based on novel technologies. The book series Power Systems is aimed at providing detailed, accurate and sound technical information about these new developments in electrical power engineering. It includes topics on power generation, storage and transmission as well as electrical machines. The monographs and advanced textbooks in this series address researchers, lecturers, industrial engineers and senior students in electrical engineering.

****Power Systems is indexed in Scopus****

Editors

David Borge-Diez and Enrique Rosales-Asensio

Energy System Resilience and Distributed Generation



Editors

David Borge-Diez

Department of Electrical Engineering, University of León,
León, Spain

Enrique Rosales-Asensio

Department of Electrical Engineering, University of Las
Palmas de Gran Canaria, Las Palmas de Gran Canaria,
Spain

ISSN 1612-1287

e-ISSN 1860-4676

Power Systems

ISBN 978-3-031-67753-3 e-ISBN 978-3-031-67754-0

<https://doi.org/10.1007/978-3-031-67754-0>

© The Editor(s) (if applicable) and The Author(s), under
exclusive license to Springer Nature Switzerland AG 2024,
corrected publication 2024

This work is subject to copyright. All rights are solely and
exclusively licensed by the Publisher, whether the whole or
part of the material is concerned, specifically the rights of
translation, reprinting, reuse of illustrations, recitation,
broadcasting, reproduction on microfilms or in any other
physical way, and transmission or information storage and
retrieval, electronic adaptation, computer software, or by
similar or dissimilar methodology now known or hereafter
developed.

The use of general descriptive names, registered names,
trademarks, service marks, etc. in this publication does not
imply, even in the absence of a specific statement, that

such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11,
6330 Cham, Switzerland

Contents

Energy Resilience: Definition and Assessment

Fellipe Sartori da Silva and José Alexandre Matelli

Adaptive Resilience Metrics for DER-Rich Electric Distribution Systems

E. Oti Boateng, Md. F. Rafy, P. Sarker, S. Basumallik and A. K. Srivastava

Maintaining Energy System Resilience Through Adaptation

Larry Hughes

External Resilience Assessment of Energy Critical Infrastructures

Martin Hromada, David Rehak, Miltiadis Kontogeorgos and Neil Walker

Enhancing Resilience of Active Distribution Networks to Extreme Weather Events Now and in the Future

Laiz Souto and Abdullallah Al-Mashhadani

Peak Load Reduction and Resilience Benefits in Critical Microgrids

Enrique Rosales-Asensio, Daniel Icaza, Noemi González-Cobos and David Borge-Diez

A Multilayer Resilience Assessment of Power Distribution Systems with Reliability Models, Service Restoration, and Dynamic Bayesian Networks

Michel Bessani, Henrique O. Caetano, N. Luiz Desuó, Matheus S. S. Fogliatto and Carlos D. Maciel

Economic and Resilience Improvement for Radial and Meshed Grids

Enrique Rosales-Asensio, Miguel de Simón-Martín, Jorge Blanes-Peiró, Alberto González-Martínez and Antonio Colmenar-Santos

Resilience Improvement in Office Buildings with Critical Loads

Enrique Rosales-Asensio, Miguel de Simón-Martín,
David Borge-Diez, Jorge Juan Blanes-Peiró and
Antonio Colmenar-Santos

Resilience Improvement in PreCOVID-19 Medical Centers

Alexis Lagrange, Miguel de Simón-Martín,
Alberto González-Martínez, Stefano Bracco and
Enrique Rosales-Asensio

Resilience Improvement in PostCOVID-19 Medical Centers

Josep Hervás-Zaragoza, Antonio Colmenar-Santos,
Enrique Rosales-Asensio and Lucía Colmenar-Fernández

Correction to: Energy Resilience: Definition and Assessment

Fellipe Sartori da Silva and José Alexandre Matelli

Energy Resilience: Definition and Assessment

Fellipe Sartori da Silva^{1, 2}  and José Alexandre Matelli¹ 

(1) Department of Chemistry and Energy, School of Engineering, São Paulo State University, Guaratinguetá, São Paulo, Brazil

(2) Department of Mechanical Engineering, Federal University of Paraná, Curitiba, Paraná, Brazil

 **Fellipe Sartori da Silva (Corresponding author)**
Email: fellipe.sartori@ufpr.br

 **José Alexandre Matelli**
Email: jose.a.matelli@unesp.br

Abstract

The concept of resilience is widely addressed within several areas, including energy one. As a recently introduced idea in the latter, its definition and analysis still varies between approaches. The aim of this chapter is to cover some of the descriptions found in literature, expliciting their common points and then converging to a single definition. Initially, this concept will be explored in the context of several systems, then advancing to engineering systems and finally to energy ones, including both generation and transmission systems. In addition, several researches addressing energy

resilience will be selected and detailed, in a way to point out some analysis patterns, focusing on two types of factors influencing the resilience assessments: the ones inboard and those abroad the system. For each type, some of the important methods will be highlighted. The important founts of the survey will be discussed and summarized, as a way to outline the context of resilience within the energy field and emphasize the most recent advances, guiding the future research.

Keywords Engineering systems resilience – Energy systems resilience – Energy resilience definition – Energy resilience assessment

The original version of the chapter has been revised: The author's name has been updated. A correction to this chapter can be found at https://doi.org/10.1007/978-3-031-67754-0_12

1 The Concept of Energy Resilience

1.1 Defining Resilience

Resilience is a widely used term among several fields, and its adoption is not recent. In material sciences, resilience is studied as a mechanical property for at least 200 years [1]. This term was firstly adapted as a system feature in 1973 by Holling, in his work addressing ecological systems [2]. Holling developed an idea that resilience is associated with the capacity of the system to absorb a disturbance and still keep its functional operation. From an ecological perspective, maintaining the relationship between populations is one of the aspects of a resilient system, according to Holling.

Since Holling work, the concept of resilience has evolved and reached several areas. Masten et al. [3] cites the psychological meaning of resilience as an individual

component, covering its well-being after threatening circumstances. This development in psychology allowed the recognition of important aspects of psychopathologies [4]. Adger [5] developed a relation between the ecological resilience (described by Holling) and a social resilience, which the author defined as a community capacity for cope with external disturbances—in the form of environmental variation or social outbreak—in its infrastructure. Urban systems, complex structures composed by important societal fields, are also theme of resilience researches [6], focusing mainly on cities improvement. Firms [7], smallholders [8], health system [9], educational system [10], farms [11], supply chain [12], Industry 5.0 [13], and many others, are examples of resilience studies subjects.

Compiled elements of different resilience studies, pointing out the area, the subject, and the external source of occurrence, are summarized in Table 1. It is interesting to note the varieties regarding both the subjects and the sources.

Table 1 Elements of resilience studies in different areas

Area	Subject	Source of disturbance	References
Biological science	Ecosystems	Climate change and anthropogenic activities	[14]
Veterinary	Goats	Heat stress	[15]
Microbiology	Organism group	Climate change	[16]
Medicine	Person	Traumatic experiences	[17]
Social sciences	Person	Life occurrences	[18]
Humanities	Local culture	Foreign cultures	[19]
Computer science	Tensor Core Units	Hardware defects	[20]
Business and Management	Supply chains	Pandemics	[21]
Engineering	Transportation infrastructure	Natural hazards	[22]

Area	Subject	Source of disturbance	References
Energy	Power distribution network	Incidents and natural disasters	[23]

Despite of the multiplicity of the applications, some elements composing the definitions tend to converge. Firstly, the concept is always applied to a subject as an intrinsic feature. This subject—a system, a community, a person, a site, a structure, etc.—presents resilience as a characteristic, a specific ability. Another common point is the premise that the subject is always in a functional steady state before the occurrence of an event. This might appear trivial, but it is not always a trait of other states during and after the disturbance. The third shared factor is the nature of the event: the disruption comes from an external source, being environmental- or man-made- caused. Finally, one last common attribute is the unexpected condition of the occurrence.

From several perspectives, it can be noted that resilience is a system feature that measures its capacity to cope with unexpected disruptions caused by external events. This definition highlights the essence of the concept, but it can still be vague in terms of exact resilience composition. This fact creates important divergences over the term, as covered by the next sections.

1.2 Dissociating Resilience from Similar Terms

Giving the yet generalized definition of resilience, it can be indeed either misinterpreted or underdefined. Several other concepts, which are also important for system analysis, might have intermingled definitions.

Holling, since the beginning of the utilization of resilience [2], aimed to distinguish it from another concept: stability. According to the author, stability is also a system aspect, which measures its capacity to achieve back a state of equilibrium after a temporary disturbance. A stable

system is able to undergo this process rapidly and without significant variations. Although both concepts are properties of the system, they measure different aspects of it facing disturbances. Holling states that a system can be resilient and unstable concomitantly. For instance, a system might be able to properly absorb the impact and stay functional after a disruption, and still exhibit significant instability during its way back to equilibrium state.

Another term potentially confused is vulnerability—which itself also presents some distinguish interpretation, depending on the author and the area. Vulnerability can be treated as the predisposition of the system to damage, which may enhance due to its exposure to a risk and its sensitivity [24, 25]. This term, however, has been developed and it continues to be complemented [26], which may contribute to this entanglement with resilience concept. Adger [27] supports this idea by stating that vulnerability and resilience present more points of convergence than divergences, as the interest by the system response to an adverse event. As a vulnerable system exhibit an unsatisfactory response to a disturbance, it is reasonable to presume that a system presenting high vulnerability also presents low resilience, i.e., they are opposing features.

An important system attribute is flexibility, which can essentially be described as its sensitivity to changes [28]. In energy systems, for instance, energy demand and fuel price are two of several sources of changes that the system must be planned to adapt [29]. A flexible system may be misleadingly classified as resilient, given the common points of both concepts. According to Nik, Perera and Chen [30], the fundamental difference between flexibility and resilience is the source of disturbance: a flexible system is prepared to cope with high-probability low-impact

scenarios, while a resilient system can face high-impact low-probability (HILP) events.

The previous explanation is similar to the conceptual difference between resilience and reliability: the characteristics of the source of disturbance. Although both approaches aim to understand system performance under disruptive scenarios, the operational environment considered by reliability analysis is specified, as well as the system functional period of time [31–33].

In a nutshell, systems presenting either high stability, flexibility or reliability, or low vulnerability, are not necessarily resilient. Figure 1 distinguish the system classification for each attribute.

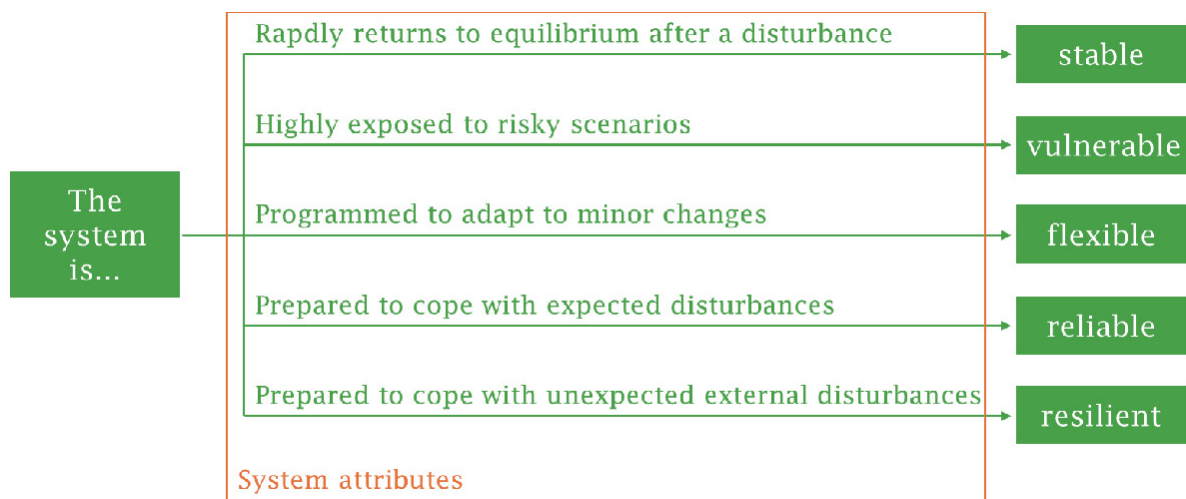


Fig. 1 System classification given its attributes

1.3 Resilience Features

It is outstanding the lack of consensus over resilience definition within scientific literature. Contributing to this scenario, several approaches addressing this topic differ when specifying resilience features. Hereafter, the content is focused on engineering systems, within the chapter scope.

In order to understand the properties, a convenient question may be asked: what does a resilient system must

present? In their work, Lin, Bie and Qiu [34] stated that the first characteristic of a resilient system is to anticipate the occurrence. This is a pre-disruption phase including system design, data analysis, capability of equipment and personnel, among others. The anticipation is also present in other resilience studies [35–37], eventually named preparedness [38].

Although the anticipation is not unanimous, the next feature is one of the most important ones: the capacity of the system to resist the disturbance maintaining some performance level. This post disruption aspect can be referred as robustness [39, 40] (the most used term for this stage [41]), standability [42], survivability [43, 44], mitigation [45], and absorptive capacity [46, 47].

At the end of the cascade failures triggered by the disturbance, a relatively robust system presents a residual performance [41]. The next phase is to withstand, i.e., to maintain this functional degree until it begins to recover. The priorities in this stage are to control the damage and to think the next steps [48]. This property is referred as response [34, 45], resourcefulness [49], and, as it takes place within a what some authors name "endure phase" [41], it can be rightly cited as endurance.

At this point, the system is functional, but its performance is degraded. It begins then the recovery phase, in which it is aimed the system to return to its normal performance, or in a near stage, as quickly as possible. Recovery (or restoration [50]) is therefore a resilience important feature [51–53].

With the partially or fully recovery, resilience analysis can continue with the system adaptation. The adaptation stage can be interpreted as a period for resilience improvement [34, 48] or system adjustment to a new normal state, post recovery [54]. The idea is to reevaluate both system condition and operational environment, which is similar to the anticipation one.

The previous mentioned features are represented in Fig. 2, following a performance path after the occurrence of an event.

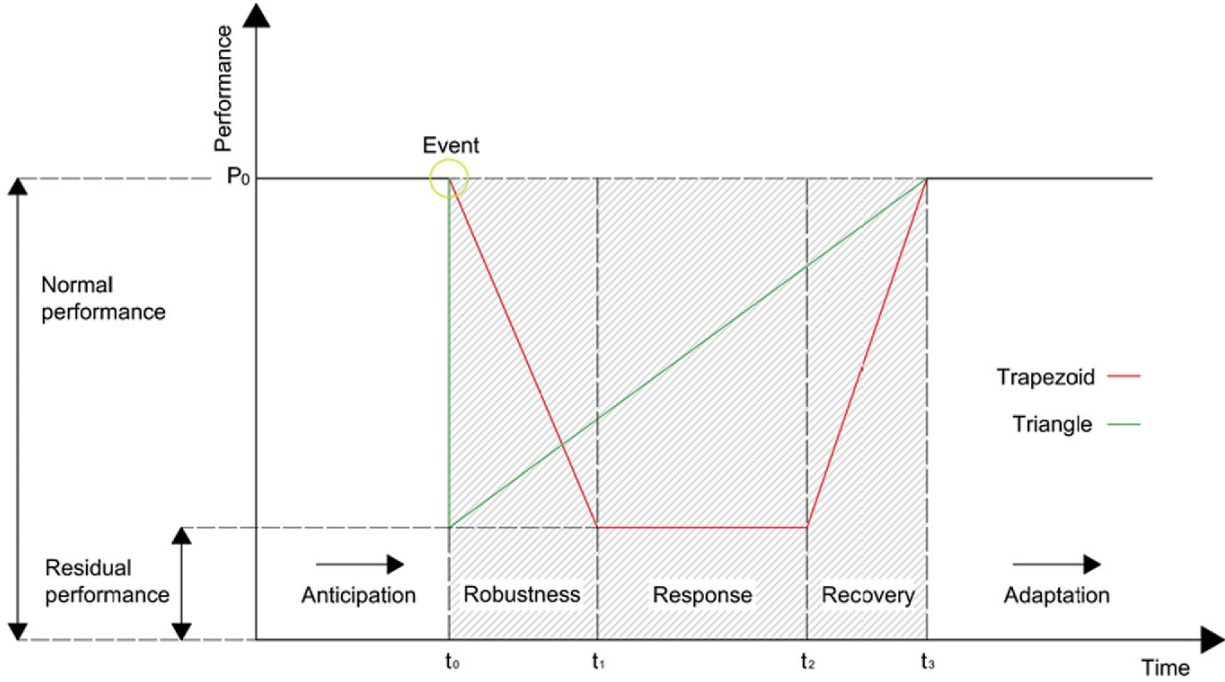


Fig. 2 Resilience curves: triangle and trapezoid.
Adapted from [55]

According to the two main approaches, the system performance can behavior as a triangle or a trapezoid after the disturbance [55]. As it can be noted in Fig. 2, in the resilience triangle the system suffers an instantaneously performance reduction until it reaches its residual value, then experiencing a linear recovery. In this analysis, the recovery follows the robustness. On the other hand, the trapezoid approach considers a period (t_0 to t_1) in which the system has its performance degraded, followed by response and recovery. In Fig. 2, both approaches present the same disruption time (t_0 to t_3) and the system is able to recover to its normal performance P_0 in the end.

The resilience features here explained—anticipation (up to t_0 in Fig. 2), robustness (t_0 to t_1), response (t_1 to t_2), recovery (t_2 to t_3), and adaptation (t_3 to next occurrence)—

are indeed the ones covered by literature, but they are often not simultaneously composing a single definition.

A report from National Infrastructure Advisory Council [48] cites robustness, resourcefulness, recovery and adaptation (named adaptability) as the resilience features. Kammouh, Gardoni and Cimellaro [56] do not consider response and adaptation in their framework. The definition explored by Steen, Ingvaldsen and Patriarca [57] excludes robustness and adaptation. Francis and Bekera [46] set anticipation (named adaptive capacity), robustness (named absorptive capacity), and recovery (named restorative capacity) as the main resilience features. Some other definitions contemplate only robustness or exclude recovery [58]. The composition of several definitions of resilience is compiled in Table 2.

Table 2 Resilience features in different researches

Anticipation	Robustness	Response	Recovery	Adaptation	References
x	✓	x	✓	✓	[59]
x	✓	x	✓	✓	[60]
✓	✓	✓	✓	✓	[61]
x	✓	x	✓	x	[62]
x	✓	x	✓	✓	[63]
x	x	x	✓	x	[64]
x	✓	x	✓	x	[65]
✓	✓	x	✓	x	[66]
x	x	✓	✓	x	[67]
x	✓	✓	✓	x	[68]

1.4 Energy Resilience

The general definitions and features of resilience suits several distinct areas and subjects, as expressed in last sections. Hereafter, the aim is to interpret this concept from energy perspective.

The utilization of the term “energy resilience” is relatively recent. It is shown in a Scopus survey that not more than 3 papers addressing this exactly term (and its synonym “energy resiliency”) were yearly published until 2014, when the number of publications significantly raised until it reaches 100 in 2023—an expressive 3.233% growth in 10 years. The publications of 2022 and 2023 count for 42% of the total amount of documents regarding this term until 2023. It is possible to conclude that energy resilience is not only recent, but surely a hot topic.

The use of resilience (or “resiliency”) within energy field as a whole also presents a recent relevant rise. The yearly publications went over 100 only in 2013, and 10 years later it reached 2.389 documents—a 1.811% growth. The amount of papers in 2023 alone represents 21% of the total amount until that year—also indicating a hot topic in this area.

Until 2010, authors adopting “energy resilience (y)” referred to a mechanical characteristic of materials. Thomas and Kerner [69] began to use the “energy resilience” in their work by contextualizing engineering resilience to energy resources of the US Department of Defense. The same essence was used by Rendall et al. [70]. The authors described a “transport energy resilience” as the ability of the transport system to adapt to fuel price shocks and constraints, inside a greater concept of “transport resilience”. In the same perspective, smart houses energy resilience was analyzed by Ghasemieh et al. [71] as their ability to deal with failures in energy distribution, and Mutani et al. [72] studied energy resilience as a feature of cities.

According to the Scopus survey, the first work addressing the term “energy resilience” to energy systems is a book by Naim Afgan [73]. Afgan defines energy resilience as *“the ability of the energy system to provide and maintain an acceptable level of service in the face of*

various challenges to normal operation". One year later, Afgan published an article with Ayfer Veziroglu paraphrasing the previous energy resilience definition [74]. Since then, the terminology has been developed and connected to energy systems.

Gatto and Drago [75] define energy resilience as *"the ability of an energy system to retain, react, overcome and overpass perturbations caused by a shock in economic, social, environmental and institutional terms, coming from the learning capacity to adapt to change"*. This definition covers part of the resilience features described in last section applied to energy systems, additionally outlining the possible sources of disturbances.

In the urban context, energy resilience was defined by Sharifi and Yamagata [76] as *"the [energy system] ability to prepare and plan for, absorb, recover from, and more successfully adapt to any disruptions that may happen in the future"*. The authors performed a robust literature review to arrange this definition, citing also the features "preparation" (similar to anticipation), absorption (robustness), recovery, and adaptation as the ones composing the concept.

It is incorrect, however, to state that the study of resilience in energy systems began in 2010's. In the 80's, for example, Kahn [77] studied some aspects of solar power generation systems and formulated a basic model for resilience analysis, a concept that the author described as *"the ability of a system to sustain basic capabilities in the face of major unanticipated disturbances"*, an adaptation of the definition given by—and already detailed here—Holling. As previously stated, the major interest in resilience within the energy field is recent, but the word was eventually adopted in the past.

From the previous descriptions, it can be seen that energy resilience presents a definition similar to resilience

alone—essentially a subject coping with external disturbances. The difference, however, is the subject of analysis. While some authors apply the term directly to energy systems, others study the system relying on energy ones as the principal. In next section, this difference supports two distinct views of energy resilience regarding energy systems: as an inboard factor and an abroad factor.

2 Assessing Energy Resilience

In general, there is no consensual method to assess resilience in engineered systems. It is natural then that several current works tend to propose a method for resilience analysis. Specifically regarding energy resilience, the development is even more recent and the assessment is yet in the early stage.

In this section, several works covering energy resilience assessment are highlighted. The main survey took place in Scopus, by searching articles in english containing in their title, abstract or keywords the term “energy resilience” or “energy resiliency”. 210 documents were found and analyzed, and the main information is presented as follows.

Two main groups were used to separate the works.

The first group, discussed in Sect. [2.1](#), considers energy resilience as an abroad factor. This characterization is based on the perspective of energy systems—the ones responsible for energy generation, transmission and distribution. If the term “energy resilience” is applied to a system that is not classified as an energy one—but, on the other hand, relies on it—, the concept is then intended to analyze an external source of energy, not the generation or transmission itself.

Contrarily, considering “energy resilience” an inboard factor means analyzing an energy system in terms of its generation, transmission or distribution. In this case, resilience is an intrinsic energy system feature. However, it

is known that other designations can also suit this evaluation, and therefore they are also considered. This classification is explored in Sect. 2.2.

2.1 A System Abroad Factor

Through a critical analysis of the 210 articles, 27 papers addressing energy resilience as an abroad factor were selected. In 14 of them, the evaluation of energy resilience was made by proposing parameters based on performance, time, supply/demand relation or other aspects; in 9 the authors developed a composite index; and in 4 it was proposed a multi-objective optimization.

2.1.1 Resilience Parameters

In some of the works, a parameter based on an important process feature is developed, in order to quantify energy resilience of different systems. Performance-based parameters stand out as one of the proposed metrics.

Energy resilience of buildings was analyzed by Kim et al. [78]. The authors proposed a photovoltaic panels cladding system (BPPL), along with storage batteries, in order to increase the contribution of renewable sources generation. They evaluate the building energy resilience by measuring the power grid inoperability, which is the lost of functionality during a power outage—or its complementary parameter, fragility X_0 . As show in Eq. 1, the fragility of the building is given by the sum of the fragilities of the grid and the BPPL.

$$(X_0)_{building} = (X_0)_{grid} + (X_0)_{BPPL} \quad (1)$$

By decreasing the building dependency of the grid, its energy resilience became higher, since a power outage due to a grid disturbance can be partially or fully attenuated by the energy from PV panels. According to the authors, an enhancement of energy resilience depends on the amount

of redundancies—which adds more terms to Eq. 1—and energy generated.

Focusing on improving the energy resilience of military bases, a parameter named Expected Electrical Distribution Mission Impact (EEDMI) was proposed by Kain et al. [79] to analyze the grid. Higher values of EEDMI to a indicate higher amount of energy not delivered (lower performance), while lower values point to a more resilient system, less susceptible to fail after an event. EEDMI is calculated according to Eq. 2. It considers the probability of occurrence of a specific threat P_r in all contemplated scenarios S , and a variable M_s , which is given by summing the values of MDI (Mission Dependency Index) during the system disturbance period. The MDI measures the criticality of infrastructures giving a particular mission. The higher the MDI and the disturbance period, the higher the M_s .

$$EEDMI = \sum_{s \in S} Pr(S = s) M_s \quad (2)$$

Also addressing energy resilience as a feature of military bases, Anuat et al. [80] studied the impact of supply chain disruptions to military microgrids. Named “energy resilience impact to microgrid”, the E_M variable is obtained by Eq. 3. In a 0-100 range, $E_M = 100$ indicates that the military base instantaneously suffers a blackout during a certain period due to supply chain disruption, while a $E_M = 0$ assures a fully functional performance of microgrid under disturbances.

$$E_M = E_C^{max} + \frac{\sum_{i=1}^N E_{C,i} - E_C^{max}}{\sum_{i=1}^N M_{C,i} - E_C^{max}} \cdot (100 - E_C^{max}) \quad (3)$$

The parameter E_C^{max} is the maximum energy resilience impact for a specific number N of critical loads. E_C^{max} is calculated by summing all the single energy resilience

impact on a critical load, named E_C . M_C is the mission impact value, which can be assigned as the MDI value, as approached by [79].

The work developed by Hu and Chang [81] addressed countries economies as the subject of energy resilience analysis. Although they considered objective and subjective factors under three dimensions—society, economy, and environment—the proposed method is based on an “energy resilience efficiency score”, here named $ERES$ and given by Eq. 4.

$$ERES = \frac{Actual\ y^d}{Target\ y^d} \quad (4)$$

The variable y^d represents a desirable outcome. Regarding all the considered features for energy resilience evaluation, a $ERES = 0$ represents a very fragile economy, while the unity points to a performance in its maximum level.

Performance and time were considered by Shandiz et al. [82] to assess energy resilience of a community by examining the power supply network during an event. The resilience indicators are the critical load not served (CLNS), given by Eq. 5 and the duration of critical load not served (DCLNS), represented in Eq. 6. $CLNS$ is a measure of the power not delivered by the system, which is basically the area above the resilience trapezoid in Fig. 2, from the initial time t_0 to the time in which the system recovers its fully performance, t_3 (or t_f , as it is assigned in the work). $DCLNS$ is the duration time of this disturbance, given by the difference between t_f and the time in which the system starts to degrade, t_1 .

$$CLNS = \int_{t_0}^{t_f} Rt\ dt \quad (5)$$

$$DCLNS = t_f - t_1 \quad (6)$$

Parameters relying on time and energy were used by Kumar and Cao [83] to analyze energy resilience of a metro railway system. The authors proposed a zero-emission train station with battery-powered trains, power sharing, and battery swapping as a projection for future developments.

During a simulated power outage, the portion of the demand met by the renewable energy generation and its storage without the necessity of the backup system is named energy-based resilience factor, R_e (Eq. 7). The period in which the system is able to fully meet the demand without backup is compared to the total amount of time in the time-based resilience factor, R_t (Eq. 8). Finally, the annual maximum energy generated by the backup is considered by the power-based resilience indicator, R_p (Eq. 9).

$$R_e = \int_0^{8760h} PO_s \cdot \left(\frac{S_{load}(t) - D_{imp}(t)}{S_{load}(t)} \right) dt \quad (7)$$

$$R_t = \left(\frac{timestep}{total\ duration} \right) \cdot \int_0^{8760h} (if\ D_{imp}(t) > 0, add\ 1) dt \quad (8)$$

$$R_p = max \int_0^{8760h} D_{imp}(t) dt \quad (9)$$

In the previous equations, PO_s is the power outage period, $S_{load}(t)$ is the load at a certain time t and $D_{imp}(t)$ is the energy generated by the backup system at t . The parameters R_e and R_t vary within the range 0–1.

Rosales-Asensio et al. [84] studied the survivability of a system as a measure of buildings energy resilience. Renewable Energy Optimization (REopt®), a National Renewable Energy Laboratory (NREL) software [85], was used for the simulation. Random blackouts striking the grid, working with energy storage, were simulated, and the period in which the grid survived was used as the resilience

evaluation. The same simulation was after applied to critical buildings [86], but focusing on supplying a critical load instead of analyzing the downtime.

The same analysis was made by Hervás-Zaragoza et al. [87]. In their study, the authors also used REopt® to simulate a hospital power demand, supplied by microgrids. For the energy resilience analysis, power outages occurred over a year and the period that the microgrid was able to survive was considered.

Parameters regarding the relation of energy demand and supply were also developed.

Anderson et al. [88] proposed a “part-time resiliency”, here named PTRes, which contemplates the amount of renewable energy (RE) generation that meet the load and the portion that can be delivered by stored energy. The authors proposed this renewable energy hybrid system (REHS) as a way to complement or replace a diesel generator, when its not partially or fully available, enhance energy resilience of buildings in general. The simulated conditions was done by using Reopt®

PTRes is calculated by Eq. 10, being S_{kWh} the amount of energy stored, and the subscripts “coinc” and “non-coinc” represents the RE generated coincident and not coincident with demand.

$$PTRes = RE_{coinc} + \min(RE_{non-coinc}, S_{kWh}) \quad (10)$$

A solar energy system integrated with a electric vehicle (EV) reserve battery (rb) is studied by Mehrjerdi [89] as a way to enhance the energy resilience of a home energy management system. By adopting this improved system, the EV is available for the whole day and the building becomes less dependent of the energy supplied by the grid.

The authors describe the system as resilient when the Eq. 11 is true, i.e., when the EV, along with the reserve battery, meet the load demand regardless of alternative sources, as power grid and solar energy. In this way, grid

disturbances or solar energy unavailability should not interfere in load demand.

$$E_{ev}^{v,w} + E_{rb}^{v,w=96} \geq P_{de}^{v,w} \quad (11)$$

The energy resilience of buildings was evaluated by Zhang et al. [90]. The authors presented resilience parameter based on energy demand and supply for a building inside a community affected by an earthquake. The energy resilience R_{sys} is presented by Eq. 12.

$$R_{sys} = 1 - \frac{L_0 R_{sys}}{\sum_{i \in N^c} \sum_{t \in 0,1,\dots,t_T} D_{it}} \quad (12)$$

In Eq. 12, the fraction denominator represents the total power demanded by the community during a certain period t_T , while the numerator exhibits the community energy system lack of resilience, which is a deficit in power delivered compared to the demanded one. The closer to the unit R_{sys} get, the higher the resilience, which means, in this case, a fully met energy demand.

Some other authors explored different features to assess energy resilience.

Ang'u et al. [91] defend energy mix diversity as a measure of energy resilience of a country. By studying electricity data of Kenya, they proposed three parameters as indicator of energy resilience. The diversity D (Eq. 13) exhibits the multifariousness of the energy mix, and its calculation depends on the amount of energy generated from each source n and from all sources N .

$$D = 1 - \left(\frac{\sum n(n-1)}{N(N-1)} \right) \quad (13)$$

The actual generated energy and the amount that could be generated at full capacity are compared by spare capacity SP (Eq. 14). It depends on the installed capacity using fuel i (GW_i), the actual electricity generated using fuel i ($GW h_i$),

the relative maximum possible generation of a power plant operating with fuel i (CF_i), and the Real Gross Domestic Product ($GDPR$).

$$SP = \frac{\sum_{i=1}^n (((GW_i \cdot hours) \cdot CF_i) - GW h_i)}{GDPR} \quad (14)$$

The last parameter is the proportion of energy exported and imported, PEI (equation 15), which relies on EIM (imported electricity), EEX (exported electricity), TEC (consumed electricity), and TEG (generated electricity). PEI also depends on ψ —equal to -1 if $EIM > EEX$ or 0 if not—and θ —equal to -1 if $EEX > EIM$ or 0 if not.

$$PEI = \left(\psi \cdot \frac{-EIM + EEX}{TEC} \right) + \left(\theta \cdot \frac{-EIM + EEX}{TEG} \right) \quad (15)$$

Office buildings were the subject of Mathew et al. [92], who proposed a energy resilience parameter named occupant hour lost, OHL . This variable measures the wasted productivity due to a power outage, in business perspective.

The authors described one of the OHL possible calculation as exhibited in Eq. 16, in which it varies within the range 0–1. The building occupants and their working time in hours, here respectively named O and t , are analyzed in two scenarios. While the usual environment considers the total amount of occupants working the full time, the lost condition accounts the occupants prevented from working during t hours due to a power outage. Another possibility of utilization of OHL is to consider only the fraction numerator, in occupant-hours.

$$OHL = \frac{lost(O \cdot t)}{usual(O \cdot t)} \quad (16)$$

2.1.2 Composite Index

A composite index is a multidimensional quantitative indicator that comprises several complex concepts [93]. The selection of indicators is the most important step of this method, as they must represent all the major influences of the index.

Three pillars—energy access, energy security, and renewable energy—were proposed by Gatto and Drago [75] in order to organize the considered indicators. Their index, named GERI (global energy resilience index), received the information of which indicator contributes positively or negatively to resilience. Then, a process of randomization of the indicators weights was simulated and repeated until it reaches the convenient number for a Monte Carlo approach. The authors applied GERI to several countries and obtained a normalized 0–100 index for each one. The authors also used this metric to analyse energy transition in China [94]. The same indicators were studied by Dong et al. [95], with the difference that these authors assigned weights and also calculated one sub-index to each pillar.

Esfandi et al. [96] proposed an index to evaluate energy resilience of urban spatial structures. Considering four components—urban geometry and morphology, land use, public transportation, and passive design—, the authors named 28 indicators and estimated their weights with factor analysis. The USSER (urban spatial structure energy resilience) was then calculated for 250 urban blocks.

By analysing some possible indicators within scientific literature, Wang et al. [97] filtered the ones that fit into three dimensions of urban energy system resilience (UESR). The dimensions are: multifarious capabilities of the energy system within a city (CE), interdependencies between other basic city subsystems and the energy system (CI), and comprehensive vulnerabilities of cities and energy (CV). Their scrutiny returned 113 indicators, which were applied to a resilience index and used for analyze 309 cities in China.

A five-dimension structure for energy resilience analysis was proposed by Li and Zhang [98]. The dimensions are: availability, diversity, economic resilience, environmental resilience, and technical resilience. Considering their positive or negative influence in energy resilience, the authors proposed a China's energy resilience index (CERI) and applied it to 30 provinces.

An energy resilience index to evaluate energy production was proposed by Jamali et al. [99]. The subjects were two producers: one relying on renewable sources and one on non-renewable. The index (R_i) contemplates six aspects: energy plant performance, energy storage, input energy dependence, distance between system and customers, recovery level, and government support level.

Urban energy resilience was also focus of the research of Zahed and Abbaspour [100]. The authors had previously used an expert survey to establish 34 sub-criteria organized into 4 mains groups: infrastructure, built environment, governance, and socio-cultural [101]. The sub-criterias were then scored based on availability, accessibility, affordability, and acceptability (4A), as a way to develop an energy resilience evaluation model. The scores were normalized, weighted, and placed from a distance to a central point in order to represent a polygon, of which the area was calculated and compared to a maximum area, then obtaining the normalized index. This model was applied to Tehran city as a case study.

A different concept of energy resilience for households was proposed by Burlinson et al. [102], defined energy price resilience. This concept is supported by two components: energy and thermal affordability and energy and financial solvency. By using data from a survey in UK, they quantified and weighted the components and found that almost 25% of the local population exhibited low energy resilience in at least one of the aspects.

By using China as a case study, Nepal et al. [103] formulated a energy resilience index for regions based on four main indicators: economic, environmental, social and energy endowment. The data analysis from 2006 to 2021 points to an overall energy resilience enhancement in China.

2.1.3 Multiobjective Optimization

The multiobjective optimization aims to find a solution to support decision-making, based on solving objective functions, which can be digitally or physically obtained [104].

Two works developed by He, Ng and Su focused on evaluate energy resilience from an economic perspective. In the first one [105], the authors proposed an energy import resilience index, aiming to make a local economy more resilient to energy supply shocks by considering several import and demand scenarios. In other work [106], the authors address an economy by considering several dependencies in its structure. Their optimization analysis led to an energy resilience index based on the expected resilience shortfalls and the expected disruption levels.

A previously proposed framework [107] was used by Uemichi et al. [108] to analyse energy resilience of buildings—specifically applied to a hospital—, considering energy supply and demand during simulated power outages in critical conditions.

Two functions were considered by Mehrjerdi [109] to assess energy resilience of buildings. The first one aims to minimize the consumed energy cost, while the other focuses on minimizing both uncertainties and the service loss after a disturbance. These two functions were then summed to form the resilience index.

2.2 A System Inboard Factor

2.2.1 Survey Results

Among the inspected works, few considered the energy resilience as an inboard factor, from the perspective of energy systems.

A resilience parameter was proposed by Afgan and Veziroglu [74] to analyze hydrogen energy systems, which include its production, usage and storage. Using the composite index approach, a metric (Eq. 17) was developed.

$$R_j = \sum_{i=1}^k w_i \int_{t=t_0}^{t_1} [100 - q_i] dt \quad (17)$$

In Eq. 17, w_i is the considered weight of each indicator q_i . These indicators tend to be stable until the occurrence of an event in t_0 , which lasts until their recovery in t_1 . The indicators were based on four pillars: economic, environmental, technological and social.

Based on the resilience trapezoid depicted in Fig. 2, Shandiz et al. [110] formulated seven metric for resilience analysis of energy systems, although it is applied in a community level. For each feature—prepare, withstand, adapt, and recover—the authors proposed time- and performance-based parameters, named: resilience length [time], rate of resilience [performance/time], resilience area [performance-time], resilience capacity [performance], total resilience length [time], total resilience area [performance-time], and total resilience capacity [performance].

Energy systems resilience against drought is evaluated by Ahmad et al. [111]. The authors formulated the maximum resilience R_{sys} in terms of minimum energy needed but not supplied ($ENNS$), which is measured as the difference between the energy supplied before and after the event. Equation 18 exhibits this formulation.

$$\max R_{sys} = \min ENNS \quad (18)$$

A similar parameter is proposed by Soualah et al. [112] to quantify energy resilience in smart grids. The energy not exchanged *ENE* considers the energy exchanged between agents, i.e., those producing and/or consuming power. In equation Eq. 19, exhibiting *ENE* quantification, ω is the space of the agents, each agent named i ; τ is the observation period, P_G and P_C are the generated and consumed power, respectively; while P_{CH} and P_{GH} represent the generated and consumed power, respectively, within a scenario with no failures.

$$ENE = \int_0^\tau \sum_{i \in \omega} |P_{GH}^i(t) - P_G^i(t)| + |P_{CH}^i(t) - P_C^i(t)| dt \quad (19)$$

Addressing energy distribution system, Khaledi and Saifoddin [113] proposed a framework to analyze energy resilience enhancement. Although the framework is composed by several formulations in a multiobjective optimization, the authors named system resilience index the recovered power value *RPV*, a costumer imposed cost in case of power outage. It is composed by both energy supplied and demanded of a bus n , P_n and w_n , respectively. The *RPV* calculation is presented in Eq. 20

$$RPV = P_n \cdot w_n \quad (20)$$

2.2.2 Other Approaches

The consideration of energy resilience as an inboard factor is not limited by this exact term. “Power resilience”, “power system resilience”, “energy system resilience” or even the type of the system concatenated with “resilience”—as microgrid resilience or power distribution system resilience—are few examples of what can be found in a survey. It is

important to highlight that the synonym “resiliency” is also used.

The consideration of resilience in energy system analysis is not as recent as to other subjects. A survey including the terms “energy system*” and “resilience” found an initial growth in 2011—even without the inclusion of the type of the system within the research.

In their review, Jasiūnas et al. [114] found that the main metrics to assess energy systems resilience rely on the resilience curve (Fig. 2), specially connecting with its geometrical parameters. Another common approach is to consider a probability as a resilience index. For instance, the probability that an event will not degrade the system performance below a critical level. Conclusively, the authors describes the similarity of such indicators with energy security ones.

Ahmadi et al. [115] describe a similar scenario. Most part of the detailed metrics explored the resilience curve by using performance parameters to calculate the resilience index (see [46, 64, 116–118]). Gasser et al. [119] reinforce this situation in their work. Moreover, the main methods described in [115] are multiobjective optimization, agent-based modeling (ABM) and stochastic modeling (SM). In ABM, several autonomous objects (agents) receive inputs and interact with each other based on identified rules, generating outputs [120]. A stochastic model, on the other hand, should consider a set of weighted probabilities to predict possible outcomes [121].

3 Summary

3.1 The Current State of Energy Resilience Assessment

3.1.1 Concept Development

The initial utilization of resilience refers to material sciences. The introduction to ecological studies by Holling allowed a novel interpretation of this term, later being widespread to several different areas. Figure 3 summarizes this temporal evolution.

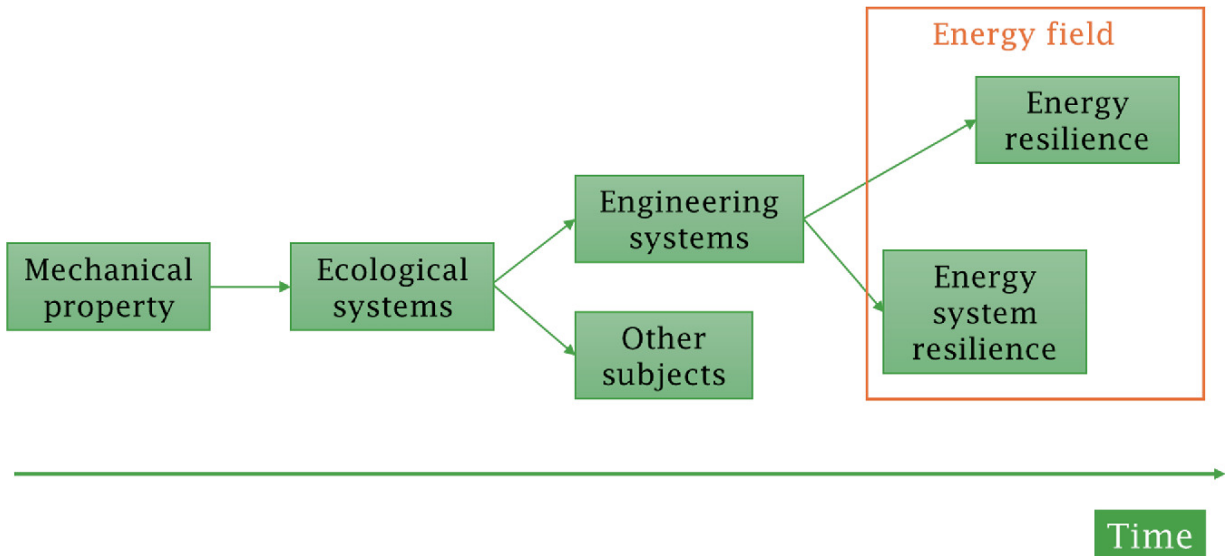


Fig. 3 Temporal evolution of the utilization of resilience

The application of resilience to engineering systems introduced the possibility to evaluate their capacity to cope with unexpected disturbances caused by external sources. Since energy resilience was assigned to energy systems by Afgan, the concept has changed and adapted to several types of occurrences and subjects. The Gatto and Drago definition, contextualizing an energy system ability, is commonly applied to structures supplied by energy—as cities and buildings—and not to energy systems themselves.

As an example of the above sentence, authors in reference [91], as described here, argue that a diversity in energy mix enhances energy resilience of a region. Hypothetically, a power plant delivering energy to a country does not necessarily need to have its resilience improved to affect the energy resilience of something. In

this case, if the whole energy infrastructure has its resilience improved (by diversification or other approaches), the country energy resilience is improved as a result. That non-resilient power plant, for which the concept was initially assigned, did not need improvement in order to the region experience the consequences. This work refers to this use of the term as an abroad factor.

Energy resilience is mostly associated with subjects relying on energy. The majority of the authors addressing this terminology applied the concept to several different systems. It is natural that energy resilience continues to be developed likewise, separating from the study of energy systems themselves. The latter can be found in literature with different denominations, as discussed in Sect. 2.2.2.

In other words, energy resilience is more usual to be assigned to cities, regions, buildings, households, and others. As its original definition still refers to energy systems, it is here proposed that researchers work to promote a new and better definition, encompassing the variety of the objects of study.

3.1.2 Assessment Frameworks

As an abroad factor, the most adopted approach is to establish a resilience parameter, based on a specific amount of energy, time, or other aspects. One of the possibilities is to simulate different scenarios and analyze a given output. REopt®, for example, is a possible tool for this purpose. Works here addressed adopted this software to analyze blackout periods, energy supplied over an assigned critical load, and renewable energy contribution to the grid. Other researches introduced backups (as energy storage systems), compared demanded and supplied energy, or composed other indicators suiting for resilience evaluation.

Composite indexes were also explored by several authors. The first ones to consider this approach were

Gatoo and Drago, by naming three pillars, each one with particular indicators. Since then, many distinct groups were proposed for energy resilience evaluation, covering divergent elements. Among the proposed groups, there are those contemplating political, social, structural, economic, environmental, and performance aspects. The most extensive proposal was developed by Wang et al. [97], after a scientific survey: 113 indicators.

The mathematical modeling of operational conditions led to this third approach: multiobjective optimization. The works here addressed aimed to minimize the damage of power outages by considering several parameters. The studied subjects were buildings and economies.

If assigned to energy systems, the energy resilience is most evaluated under the perspective of the resilience curve, from which many metrics have emerged. Performance-based and time-based parameters are then attractive ways of evaluation.

3.2 A Discussion Over the Aspects Influencing Energy Resilience

As discussed, energy resilience is a relatively recent concept, and therefore there is no standard method to its evaluation. However, based on its features, it is possible to recommend some actions that can potentially improve it.

One of the most common procedure to enhance energy resilience is to add redundancy. Including storage and other sources of energy supply can prevent power outages, changing fuel scenarios, or damage in power nodes [122]. Gilbert and Bazilian [123] highlight the necessity of considering demand disruption to energy resilience evaluation, which can be fulfilled with the addition of storage systems. As stored energy can be quickly released, it suits in case of sudden outages and changes in demand [124].

Harsini [125] presented a improved energy resilience of districts with a multi-level storage with battery, capacitor, hydropower and electric vehicles. During the load and price peaks or outages, there are redundancies that can supply the demanded energy. Solar-powered battery systems were used by Sperry et al. [126] as a way to improve energy resilience of households in Guatemala and Puerto Rico. Hydrogen fuel cells were also studied as a backup system for this purpose [127].

The same intention can be achieved by considering diversity. From a regional perspective, the highest the independence of external suppliers, the highest the energy resilience [128]. Therefore, avoiding the dependency of energy generated by few sources is one of the keys to achieve high energy resilience [129]. If the diversification is accomplished by enhancing the renewable generation, the whole grid resilience can be improved, once it reduces the demand of primary sources and relief the grid stress [130, 131].

Considering household energy resilience, Hasselqvist et al. [132] propose some ideas comprised into four main groups: backup energy sources, energy efficiency, flexibility, and energy sufficiency. The backup system, which can be battery-based, suit as the secondary electricity source. The reduction of demand is considered in energy efficiency group, by increasing this parameter of products and processes; and in energy sufficiency, by considering short and long term. In flexibility, the demand adaptation is analyzed, in order to adjust to the current supply.

Mutani et al. [72] argue that a demand reduction, along with higher contribution of renewable sources and affordable costs are keys to assure a city energy resilience. Environmental, economic, social, and government aspects are explored in the work as potential source of impacts on resilience.

In a nutshell, several works in literature endorse redundancy and diversity (prioritizing renewable sources) as the main aspects to enhance energy resilience. It is also important to attenuate socio-political, economic and environmental changes, in order to decrease the potential risks. Up to this point, there is no standard indicators to analyze energy resilience.

4 Conclusion

The concept of energy resilience, along with proposed metrics for its quantification from the perspective of several subjects were discussed herein.

Resilience is a term used in material sciences at least for 200 years, and it was only recently introduced in other areas, including engineering and energy. In this scenario, the terminology “energy resilience” has emerged, being its definition still in development phase. Therefore, it is important to delimit energy resilience, separating it from similar terms, as stability, vulnerability, flexibility, and reliability.

A general definition of resilience can be originated from the common points of several works: an intrinsic system feature that measure its capacity to cope with unexpected disruptions caused by external events. Although it is not consensual the exact resilience features, five aspects can be highlighted as the ones covered by scientific literature: anticipation, robustness, response, recovery, and adaptation.

Energy resilience is a variation of resilience addressing energy features, either within energy systems (as an inboard factor) or in structures relying on energy (as an abroad factor). The latter is the most explored approach, which indicates that future research will continue to refer to this term as an abroad factor. For energy systems, other terminologies as “power resilience”, “power system

resilience”, “energy system resilience”, and alternative related designations emerged.

As an abroad factor, energy resilience is investigated in several subjects, as buildings, regions, structures, and households. The most explored assessment frameworks are the ones introducing related parameters (as performance- or time-based), or relying on composite index (considering several indicators organized in main groups), and multiobjective optimization.

If energy systems are analyzed, the metrics often rely on resilience curve, from which emerge performance- or time-based parameters. Other methods, however, are also being explored, and a deeper investigation in this area should be conducted in order to delimit a greater scenario.

It is clear that energy resilience requires a greater and more embracing definition, which authors in future works should consider to establish. At the same time, the development of new metrics, along with the comparison and validation with actual proposed metrics, is essential to standardize its evaluation. The application of different analyses to the same subjects is also appreciated, in other to verify if the elements considered by distinct authors lead to the same conclusion. Knowing the relevant aspects of energy resilience is crucial to develop accurate metrics for its analysis.

References

1. Thurston RH (1874) On the strength, elasticity, ductility and resilience of materials of machine construction. *J Franklin Inst* 97(5):344–356
2. Holling CS (1973) Resilience and stability of ecological systems. *Annu Rev Ecol System* 4(1):1–23
3. Masten AS, Best KM, Garmezy N (1990) Resilience and development: contributions from the study of children who overcome adversity. *Dev Psychopathol* 2(4):425–444

4. Masten AS, Lucke CM, Nelson KM, Stallworthy IC (2021) Resilience in development and psychopathology: multisystem perspectives. *Annu Rev Clin Psychol* 17:521-549
5. Adger WN (2000) Social and ecological resilience: are they related? *Progr Human Geogr* 24(3):347-364
6. Meerow S, Newell JP, Stults M (2016) Defining urban resilience: a review. *Landsc Urban Plan* 147:38-49
7. Conz E, Lamb PW, De Massis A (2020) Practicing resilience in family firms: An investigation through phenomenography. *Journal of Family Business Strategy* 11(2):100355
8. Bravo-Peña F, Yoder L (2024) Agrobiodiversity and smallholder resilience: a scoping review. *J Environ Manage* 351:119882
9. Witter S, Thomas S, Topp SM, Barasa E, Chopra M, Cobos D, Blanchet K, Teddy G, Atun R, Ager A (2023) Health system resilience: a critical review and reconceptualisation. *Lancet Glob Health* 11(9):e1454-e1458
10. Dülks J, Fekete A, Karutz H, Kaufmann J, Posingies C (2023) Identification of methodologies to quantify education system resilience-a scoping review. *Int J Dis Risk Red* 103967
11. Taghipoor M, Pastell M, Martin O, Ba HN, van Milgen J, Doeschl-Wilson A, Loncke C, Friggens N, Puillet L, Muñoz-Tamayo R (2023) Animal board invited review: quantification of resilience in farm animals. *Animal* 17(9):100925
12. Carissimi MC, Creazza A, Colicchia C (2023) Crossing the chasm: investigating the relationship between sustainability and resilience in supply chain management. *Clean Logist Supply Chain* 7:100098
13. Leng J, Zhong Y, Lin Z, Xu K, Mourtzis D, Zhou X, Zheng P, Liu Q, Zhao JL, Shen W (2023) Towards resilience in Industry 5.0: A decentralized autonomous manufacturing paradigm. *J Manuf Syst* 71:95-114
14. Sánchez-Pinillos M, Dakos V, Kéfi S (2024) Ecological dynamic regimes: a key concept for assessing ecological resilience. *Biol Conserv* 289:110409
15. El-Sherbiny HR, Hashem NM, Abdelnaby EA (2023) Coat color affects the resilience against heat stress impacts on testicular hemodynamics, reproductive hormones, and semen quality in baladi goats. *BMC Vet Res* 19(1):107
16. Virta L, Hedberg P, Declining salinity and increasing temperature reduce the diversity and resilience of benthic diatoms. *Environ Microbiol*

17. Karska J, Rejek M, Misiak B (2024) Resilience buffers the association between psychotic-like experiences and suicide risk: a prospective study from a non-clinical sample. *BMC Psychiatry* 24(1):32
18. Khahan N-N, Vrabcová P, Prompong T, Nattapong T (2024) Moderating effects of resilience on the relationship between self-leadership and innovative work behavior. *Sustain Fut* 7:100148
19. Hanif M, Parji Maruti ES, Wahyuni RS (2024) Cultural resilience study: the role of the temanten mandi ritual in Sendang Modo on the survival of the surrounding community. *Cogent Arts Human* 11(1):2304401
20. Limas Sierra R, Guerrero-Balaguera JD, Condia JE, Sonza Reorda M (2024) Exploring hardware fault impacts on different real number representations of the structural resilience of tcus in gpus. *Electronics* 13(3):578
21. Sharma B, Mittal ML, Soni G, Ramtiyal B (2023) An implementation framework for resiliency assessment in a supply chain. *Glob J Flexible Syst Manage* 24(4):591-614
22. Godazgar B, Balomenos GP, Tighe SL (2023) Resilience surface for quantifying hazard resiliency of transportation infrastructure. *Resil Cities Struct* 2(3):74-86
23. Mohan G, Bhende C (2023) Resiliency enhancement of distribution network with distributed scheduling algorithm. *Electr Power Syst Res* 225:109796
24. Cutter SL, Barnes L, Berry M, Burton C, Evans E, Tate E, Webb J (2008) A place-based model for understanding community resilience to natural disasters. *Glob Environ Change* 18(4):598-606
25. Amaral C, Poulter B, Lagomasino D, Fatoyinbo T, Taillie P, Lizcano G, Canty S, Silveira JAH, Teutli-Hernández C, Cifuentes-Jara M et al (2023) Drivers of mangrove vulnerability and resilience to tropical cyclones in the north Atlantic basin. *Sci Total Environ* 898:165413
26. Naylor A, Ford J, Pearce T, Van Alstine J (2020) Conceptualizing climate vulnerability in complex adaptive systems. *One Earth* 2(5):444-454
27. Adger WN (2006) Vulnerability. *Glob Environ Change* 16(3):268-281
28. Lafou M, Mathieu L, Pois S, Alochet M (2016) Manufacturing system flexibility: product flexibility assessment. *Procedia Cirp* 41:99-104
29. Babatunde OM, Munda JL, Hamam Y (2020) Power system flexibility: a review. *Energy Rep* 6:101-106

30. Nik VM, Perera AT, Chen D (2021) Towards climate resilient urban energy systems: a review. *Natl Sci Rev* 8(3):nwaa134
31. Corotis RB (2011) Conceptual and analytical differences between resiliency and reliability for seismic hazards. In: *Structures congress*, pp 2010–2020
32. Xing L (2020) Cascading failures in internet of things: review and perspectives on reliability and resilience. *IEEE Internet of Things J* 8(1):44–64
33. Hossain E, Roy S, Mohammad N, Nawar N, Dipta DR (2021) Metrics and enhancement strategies for grid resilience and reliability during natural disasters. *Appl Energy* 290:116709
34. Lin Y, Bie Z, Qiu A (2018) A review of key strategies in realizing power system resilience. *Glob Energy Interconnect* 1(1):70–78
35. Woods DD (2017) Resilience and the ability to anticipate. In: *Resilience engineering in practice*. CRC Press, pp 121–125
36. Borg N, Naderpajouh N, Scott-Young CM, Borg J (2022) An interdisciplinary and multi-level review of resilience to inform training of human resources for critical infrastructure. *Int J Dis Risk Reduct* 78:103113
37. Geng S, Yang M, Mitici M, Liu S (2023) A resilience assessment framework for complex engineered systems using graphical evaluation and review technique (gert). *Reliab Eng Syst Saf* 236:109298
38. Orlando B, Tortora D, Pezzi A, Bitbol-Saba N (2022) The disruption of the international supply chain: Firm resilience and knowledge preparedness to tackle the covid-19 outbreak. *J Int Manage* 28(1):100876
39. Cimellaro GP, Reinhorn AM, Bruneau M (2010) Framework for analytical quantification of disaster resilience. *Eng Struct* 32(11):3639–3649
40. Cassottana B, Shen L, Tang LC (2019) Modeling the recovery process: a key dimension of resilience. *Reliab Eng Syst Saf* 190:106528
41. Poulin C, Kane MB (2021) Infrastructure resilience curves: performance measures and summary metrics. *Reliab Eng Syst Saf* 216:107926
42. Younesi A, Shayeghi H, Wang Z, Siano P, Mehrizi-Sani A, Safari A (2022) Trends in modern power systems resilience: state-of-the-art review. *Renew Sustain Energy Rev* 162:112397
43. Besharati Rad Z, Eshraghniaie Jahromi A (2014) A framework for resiliency assessment of power communication networks. *Scientia Iranica*

21(6):2399-2418

44. Vesey F, Hoseyni SM, Cordiner J (2023) Development of an industrially applicable model for the qualitative resilience assessment of process systems at the early design stage. *J Loss Prev Process Ind* 86:105199
45. Slivkova S, Rehak D, Nesporova V, Dopaterova M (2017) Correlation of core areas determining the resilience of critical infrastructure. *Procedia Eng* 192:812-817
46. Francis R, Bekera B (2014) A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliab Eng Syst Saf* 121:90-103
47. Leštáková M, Logan KT, Rehm I-S, Pelz PF, Friesen J (2023) Do resilience metrics of water distribution systems really assess resilience? A critical review. *Water Res* 2:120820
48. Council NIA (2010) A framework for establishing critical infrastructure resilience goals final report and recommendations by the council
49. Panteli M, Mancarella P (2015) Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events. *IEEE Syst J* 11(3):1733-1742
50. Yodo N, Wang P (2016) Resilience analysis for complex supply chain systems using Bayesian networks. In: 54th AIAA aerospace sciences meeting, p 0474
51. Yodo N, Wang P (2016) Engineering resilience quantification and system design implications: a literature survey. *J Mech Des* 138(11):111408
52. Sharma N, Tabandeh A, Gardoni P (2018) Resilience analysis: a mathematical formulation to model resilience of engineering systems. *Sustain Resil Infrastruct* 3(2):49-67
53. Feng Q, Liu M, Dui H, Cai B, Fan D, Ren Y, Wang Z (2024) A general design-oriented resilience measurement and evaluation method for engineering systems: resilience cube. *Reliab Eng Syst Saf* 245:110038
54. Hughes L (2015) The effects of event occurrence and duration on resilience and adaptation in energy systems. *Energy* 84:443-454
55. Li B, Mostafavi A (2024) Unraveling fundamental properties of power system resilience curves using unsupervised machine learning. *Energy AI* 16:100351
56. Kammouh O, Gardoni P, Cimellaro GP (2020) Probabilistic framework to evaluate the resilience of engineering systems using Bayesian and dynamic Bayesian networks. *Reliab Eng Syst Saf* 198:106813

57. Steen R, Ingvaldsen G, Patriarca R (2021) Engineering resilience in a prison's performance management system. *Saf Sci* 142:105367
58. Haimes YY (2009) On the definition of resilience in systems. *Risk Anal Int J* 29(4):498-501
59. Patriarca R, De Paolis A, Costantino F, Di Gravio G (2021) Simulation model for simple yet robust resilience assessment metrics for engineered systems. *Reliab Eng Syst Saf* 209:107467
60. Yarveisy R, Gao C, Khan F (2020) A simple yet robust resilience assessment metrics. *Reliab Eng Syst Saf* 197:106810
61. Ayyub BM (2014) Systems resilience for multihazard environments: definition, metrics, and valuation for decision making. *Risk Anal* 34(2):340-355
62. Dehghani F, Mohammadi M, Karimi M (2023) Age-dependent resilience assessment and quantification of distribution systems under extreme weather events. *Int J Electr Power Energy Syst* 150:109089
63. Sun H, Yang M, Wang H (2024) An integrated approach to quantitative resilience assessment in process systems. *Reliab Eng Syst Saf* 243:109878
64. Henry D, Ramirez-Marquez JE (2012) Generic metrics and quantitative approaches for system resilience as a function of time. *Reliab Eng Syst Saf* 99:114-122
65. Uday P, Marais KB (2014) Resilience-based system importance measures for system-of-systems. *Procedia Comput Sci* 28:257-264
66. Shi Q, Liu W, Zeng B, Hui H, Li F (2022) Enhancing distribution system resilience against extreme weather events: concept review, algorithm summary, and future vision. *Int J Electr Power Energy Syst* 138:107860
67. Ranasinghe U, Jefferies M, Davis P, Pillay M (2020) Resilience engineering indicators and safety management: a systematic review. *Saf Health Work* 11(2):127-135
68. Abimbola M, Khan F (2019) Resilience modeling of engineering systems using dynamic object-oriented Bayesian network approach. *Comput Industr Eng* 130:108-118
69. Thomas S, Kerner D (2010) Defense energy resilience: lessons from ecology, no 39, Strategic Studies Institute
70. Rendall S, Page S, Reitsma F, Van Houten E, Krumdieck S (2011) Quantifying transport energy resilience: active mode accessibility. *Transp Res Rec* 2242(1):72-80

71. Ghasemieh H, Haverkort BR, Jongerden MR, Remke A (2015) Energy resilience modelling for smart houses. In: 2015 45th Annual IEEE/IFIP international conference on dependable systems and networks. IEEE, pp 275–286
72. Mutani G, Todeschi V, Beltramino S (2020) Energy consumption models at urban scale to measure energy resilience. *Sustainability* 12(14):5678
73. Afgan N (2010) Sustainable resilience of energy systems. Nova Science Publishers
74. Afgan N, Veziroglu A (2012) Sustainable resilience of hydrogen energy system. *Int J Hydrogen Energy* 37(7):5461–5467
75. Gatto A, Drago C (2020) Measuring and modeling energy resilience. *Ecol Econ* 172:106527
76. Sharifi A, Yamagata Y (2016) Principles and criteria for assessing urban energy resilience: a literature review. *Renew Sustain Energy Rev* 60:1654–1677
77. Kahn E (1980) Reliability planning for solar electric power generation. *Technol Forecast Soc Change* 18(4):359–377
[[MathSciNet](#)]
78. Kim AA, Reed DA, Choe Y, Wang S, Recart C (2019) New building cladding system using independent tilted BIPV panels with battery storage capability. *Sustainability* 11(20):5546
79. Kain A, Van Bossuyt DL, Pollman A (2021) Investigation of nanogrids for improved navy installation energy resilience. *Appl Sci* 11(9):4298
80. Anuat E, Van Bossuyt DL, Pollman A (2021) Energy resilience impact of supply chain network disruption to military microgrids. *Infrastructures* 7(1):4
81. Hu J-L, Chang T-Y (2023) Energy resilience: a cross-economy comparison. *Energies* 16(5):2214
82. Shandiz SC, Rismanchi B, Foliente G, Aye L (2023) A model for energy master planning and resilience assessment of net-zero emissions community. *Sustain Resilient Infrastruct* 8(4):375–399
83. Kumar GMS, Cao S (2024) Quantifying and enhancing the energy resilience of zero-emission train station systems against power outages via electrified train-building integrations. *Energy Conv Manage X* 22:100531

84. Rosales-Asensio E, de Simón-Martín M, Borge-Diez D, Blanes-Peiró JJ, Colmenar-Santos A (2019) Microgrids with energy storage systems as a means to increase power resilience: an application to office buildings. *Energy* 172:1005–1015
85. N. R. E. Laboratory, <https://reopt.nrel.gov/tool>Reopt: Renewable energy integration & optimization. <https://reopt.nrel.gov/tool>
86. Rosales-Asensio E, de Loma-Osorio I, Açikkalp E, Borge-Diez D (2023) Biomethane microturbines as a storage-free dispatchable solution for resilient critical buildings. *Buildings* 13(10):2516
87. Hervás-Zaragoza J, Colmenar-Santos A, Rosales-Asensio E, Colmenar-Fernández L (2022) Microgrids as a mechanism for improving energy resilience during grid outages: a post covid-19 case study for hospitals. *Renew Energy* 199:308–319
88. Anderson K, Laws ND, Marr S, Lisell L, Jimenez T, Case T, Li X, Lohmann D, Cutler D (2018) Quantifying and monetizing renewable energy resiliency. *Sustainability* 10(4):933
89. Mehrjerdi H (2021) Resilience oriented vehicle-to-home operation based on battery swapping mechanism. *Energy* 218:119528
90. Zhang Z, Li S, Chen A, Jin X, Lan J, Liu Y, Wei H-H (2023) Enhancing buildings' energy resilience by dynamic seismic emergency inspection and restoration scheduling in multiple systems. *Buildings* 13(10):2610
91. Ang'u C, Muthama NJ, Oludhe C, Chitedze I (2020) The role of diversity, reserve margin and system structure on retail electricity tariffs in Kenya. *Heliyon* 6(8)
92. Mathew P, Sanchez L, Lee SH, Walter T (2021) Assessing the energy resilience of office buildings: development and testing of a simplified metric for real estate stakeholders. *Buildings* 11(3):96
93. Shah S, Zhou P, Walasai G, Mohsin M (2019) Energy security and environmental sustainability index of south Asian countries: a composite index approach. *Ecol Ind* 106:105507
94. Gatto A, Drago C, Panarello D, Aldieri L (2023) Energy transition in China: assessing progress in sustainable development and resilience directions. *Int Econ* 176:100450
95. Dong K, Dong X, Jiang Q, Zhao J (2021) Assessing energy resilience and its greenhouse effect: a global perspective. *Energy Econ* 104:105659
96. Esfandi S, Rahmdel L, Nourian F, Sharifi A (2022) The role of urban spatial structure in energy resilience: an integrated assessment

- framework using a hybrid factor analysis and analytic network process model. *Sustain Cities Soc* 76:103458
97. Wang Z, Chen Z, Ma C, Wennersten R, Sun Q (2022) Nationwide evaluation of urban energy system resilience in china using a comprehensive index method. *Sustainability* 14(4):2077
 98. Li P, Zhang J (2023) China's inter-provincial energy security resilience assessment over space and time: an improved gray relational projection model. *Energies* 16(7):3131
 99. Jamali M-B, Rasti-Barzoki M, Altmann J (2023) A game-theoretic approach for investigating the competition between energy producers under the energy resilience index: a case study of Iran. *Sustain Cities Soc* 95:104598
 100. Mohaghegh Zahed L, Abbaspour M (2023) Determination and prioritization of criteria to design urban energy resilience conceptual model (part 2). *Int J Environ Sci Technol* 20(9):9649–9662
 101. Mohaghegh Zahed L, Abbaspour M, Ghodoosi J, Sharifi A (2022) Determination and prioritization of criteria to design urban energy resilience conceptual model (Part 1). *Int J Environ Sci Technol* 19(5):3593–3606
 102. Burlinson A, Davillas A, Giulietti M, Price CW (2024) Household energy price resilience in the face of gas and electricity market crises. *Energy Econ* 132:107414
 103. Nepal R, Zhao X, Liu Y, Dong K (2024) Can green finance strengthen energy resilience? The case of China. *Technol Forecast Soc Change* 202:123302
 104. Emmerich MT, Deutz AH (2018) A tutorial on multiobjective optimization: fundamentals and evolutionary methods. *Natural Comput* 17:585–609 [[MathSciNet](#)]
 105. He P, Ng TS, Su B (2015) Energy import resilience with input-output linear programming models. *Energy Econ* 50:215–226
 106. He P, Ng TS, Su B (2019) Energy-economic resilience with multi-region input-output linear programming models. *Energy Econ* 84:104569
 107. Uemichi A, Yagi M, Oikawa R, Yamasaki Y, Kaneko S (2019) Multi-objective optimization to determine installation capacity of distributed power generation equipment considering energy-resilience against disasters. *Energy Procedia* 158:6538–6543
 108. Uemichi A, Kaito N, Yamasaki Y, Kaneko S (2023) Practical method for optimizing capacities of private generators installed in hospital buildings

- during power outages. *J Energy Resour Technol* 145(2):022105
109. Mehrjerdi H, Resilience-uncertainty nexus in building energy management integrated with solar system and battery storage. *IEEE Access*
 110. Shandiz SC, Foliente G, Rismanchi B, Wachtel A, Jeffers RF (2020) Resilience framework and metrics for energy master planning of communities. *Energy* 203:117856
 111. Ahmadi S, Saboohi Y, Tsatsaronis G, Vakili A (2021) Energy system improvement planning under drought condition based on a two-stage optimization model: the desire for sustainability through the promoting of system's resilience. *Energy Rep* 7:3556–3569
 112. Soualah H, Jodin G, Le Goff Latimier R, Ben Ahmed H (2023) Energy not exchanged: a metric to quantify energy resilience in smart grids. *Sustainability* 15(3):2596
 113. Khaledi A, Saifoddin A (2023) Three-stage resilience-oriented active distribution systems operation after natural disasters. *Energy* 282:128360
 114. Jasiūnas J, Lund PD, Mikkola J (2021) Energy system resilience-a review. *Renew Sustain Energy Rev* 150:111476
 115. Ahmadi S, Saboohi Y, Vakili A (2021) Frameworks, quantitative indicators, characters, and modeling approaches to analysis of energy system resilience: a review. *Renew Sustain Energy Rev* 144:110988
 116. Bruneau M, Chang SE, Eguchi RT, Lee GC, O'Rourke TD, Reinhorn AM, Shinozuka M, Tierney K, Wallace WA, Von Winterfeldt D (2003) A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthq Spectra* 19(4):733–752
 117. Gong J, You F (2018) Resilient design and operations of process systems: nonlinear adaptive robust optimization model and algorithm for resilience analysis and enhancement. *Comput Chem Eng* 116:231–252
 118. Ouyang M, Duenas-Osorio L (2014) Multi-dimensional hurricane resilience assessment of electric power systems. *Struct Saf* 48:15–24
 119. Gasser P, Lustenberger P, Cinelli M, Kim W, Spada M, Burgherr P, Hirschberg S, Stojadinovic B, Sun TY (2021) A review on resilience assessment of energy systems. *Sustain Resil Infrastruct* 6(5):273–299
 120. De Marchi S, Page SE (2014) Agent-based models. *Annu Rev Polit Sci* 17:1–20
 121. Pinsky M, Karlin S (2010) An introduction to stochastic modeling. Academic press

122. Katalenich SM, Jacobson MZ (2023) Renewable energy and energy storage to offset diesel generators at expeditionary contingency bases. *J Def Model Simul* 20(2):213–228
123. Gilbert AQ, Bazilian MD (2020) The covid-19 pandemic: energy market disruptions and resilience. *J Crit Infrast Policy* 1(2):73–83
124. Gupta R, Bruce-Konuah A, Howard A (2019) Achieving energy resilience through smart storage of solar electricity at dwelling and community level. *Energy Build* 195:1–15
125. Harsini AE (2023) Resilience-oriented district energy system integrated with renewable energy and multi-level seasonal energy storage. *J Energy Storage* 72:108645
126. Sperry BM, Dou FY, Dillon T, Tatum WK, Chapko MK, Pozzo LD (2023) Combating energy poverty via small-scale solar for initial electrification and post-disaster recovery in guatemala and puerto rico communities. *Energy Sustain Dev* 76:101291
127. Tziritas D, Stavrakakis GM, Bakirtzis D, Kaplanis G, Patlitzianas K, Damasiotis M, Zervas PL (2023) Techno-economic analysis of a hydrogen-based power supply backup system for tertiary sector buildings: a case study in greece. *Sustainability* 15(9):7646
128. Janota L, Vávrová K, Bízková R (2023) Methodology for strengthening energy resilience with smart solution approach of rural areas: Local production of alternative biomass fuel within renewable energy community. *Energy Rep* 10:1211–1227
129. Jing R, Lin Y, Khanna N, Chen X, Wang M, Liu J, Lin J (2021) Balancing the energy trilemma in energy system planning of coastal cities. *Appl Energy* 283:116222
130. Speake A, Donohoo-Vallett P, Wilson E, Chen E, Christensen C (2020) Residential natural gas demand response potential during extreme cold events in electricity-gas coupled energy systems. *Energies* 13(19):5192
131. Shamoushaki M, Koh SL (2023) Heat pump supply chain environmental impact reduction to improve the UK energy sustainability, resiliency and security. *Sci Rep* 13(1):20633
132. Hasselqvist H, Renström S, Strömberg H, Håkansson M (2022) Household energy resilience: shifting perspectives to reveal opportunities for renewable energy futures in affluent contexts. *Energy Res Soc Sci* 88:102498

Adaptive Resilience Metrics for DER-Rich Electric Distribution Systems

E. Oti Boateng¹, Md. F. Rafy¹, P. Sarker², S. Basumallik¹ and A. K. Srivastava¹ 

(1) Smart Grid Resilience and Analytics Lab, West Virginia University, Morgantown, WV, USA

(2) Smart Grid Resilience and Analytics Lab, WV and Dominion Energy, Richmond, VA, USA

 **A. K. Srivastava**

Email: anurag.srivastava@mail.wvu.edu

Abstract

Distributed Energy Resources (DERs) offer a diverse and adaptable set of capabilities to address energy demands in a resilient, economical and environmentally sustainable manner. Further, the adoption of DERs enables the integration of advanced technologies, including smart meters, energy storage, and demand response systems, which contribute to a more practical and adaptive approach to electricity distribution. However, the integration of DERs poses challenges such as grid stability and voltage regulation issues, following the addition of diverse generation sources and advanced technologies.

Additionally, the increase in frequency of extreme events, such as cyberattacks, presents a risk to DER-rich systems, and this emphasizes the need for resilience. One major challenge with resilience is interdisciplinary aspects, and no standardized methodology for assessing resilience. Without established guidelines, researchers may take divergent approaches, making it difficult to compare findings and draw practical conclusions. Additionally, current approaches to resilience rely heavily on historical data and fail to capture the broader dimensions of resilience, rendering them insufficient and less adaptive to the dynamic and evolving nature of threats. This work (a) develops a resilience taxonomy and categorizes resilience metrics for distribution systems to highlight the limits of current resilience evaluation methodologies. (b) proposes adaptive resilience metrics, with use cases, to assess and improve system resilience to evolving operational conditions and potential threats, (c) discusses use case results and key considerations for practical resilience metrics.

Keywords Adaptive resilience – Resilience metrics – Resilience taxonomy – Distribution system – AWR metrics – Cyber-physical resilience – Internet of things

1 Introduction

1.1 Evolving DER-Rich Distribution Grid

The renewable energy roadmap [1] forecasts the global adoption of renewable energy resources to increase from 24 to 85% by 2050. To achieve this, the integration of distributed energy resources (DER) is expected to play a pivotal role in this transition, facilitating greater flexibility and resilience in energy systems worldwide. DERs can include rooftop solar panels and other small-scale inverter-

based resources, micro-turbines, diesel generators, electric vehicles, and battery storage systems. The DER-rich distribution system aims to provide multiple advantages [2] (Fig. 1):

1. *Peak Load Reduction*: DERs help in mitigating peak demand by providing localized energy generation and storage solutions.
2. *Decentralization*: DERs promote a decentralized energy system, reducing reliance on centralized power plants and enhancing grid resilience.
3. *Lower Energy Costs*: Through measures such as demand response and energy efficiency, DERs help users lower energy costs for customers. Household consumers are combining energy storage systems with solar panels to decrease their electricity consumption during periods of elevated electricity prices.
4. *Resilience to Disasters*: Distributed generation and storage enhance resilience to natural disasters and grid outages by providing localized electric supply.
5. *Flexibility and Adaptability*: DERs offer flexibility in responding to changing energy demands and market conditions, allowing for dynamic energy management strategies.

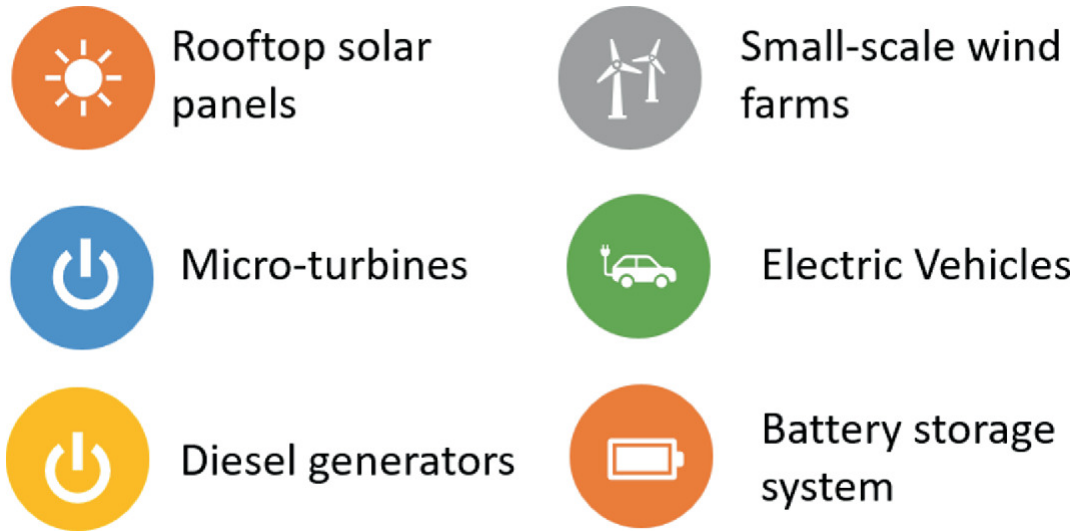


Fig. 1 Different types of DERs in distribution system

To integrate these vast number of DERs, smart distribution systems are using advanced communication and automated controls. Monitoring and situational awareness are facilitated by high-speed data from Remote Terminal Units (RTUs), which typically take a few minutes to transmit information, Supervisory Control and Data Acquisition (SCADA) systems, which operate with a latency of a few seconds, and micro-phasor measurement units (μ -PMUs), capable of providing 60–120 samples per second.

However, the introduction of DERs has its own challenges and has significantly increased the complexity of electric distribution systems [3, 4]. The variability of generation from photovoltaic panels and other renewable sources often results in fluctuating and uncontrollable power generation that can cause rapid imbalances between generation and locally consumed power [4]. Additionally, the low or non-existent system inertia resulting from DERs further complicates grid stability and control. In cases of high DER penetration, maintaining voltage within limits becomes increasingly challenging. Lastly, increased digitalization in DERs also exposes them to cybersecurity threats [5].

1.2 Increasing Number of Weather and Cyber Events and Grid Resilience

The increase in weather and cyber events has significant impacts on the resilience of electric distribution system [6–8]. According to the IEEE standard IEEE-346-1973, weather conditions are categorized into three distinct types: normal, adverse, and major, each with varying degrees of impact on the environment and infrastructure [9]. Some of the major weather events that adversely affect the resilience of distribution systems include hurricanes, tornadoes, winter storms, wildfires, and flooding. The following are examples of some events that have caused large scale outages:

1. Superstorm Sandy [10]: over 8 million customers lost electric access across multiple states in the United States.
2. Tapani storm [11]: caused large-scale blackouts lasting up to three weeks in Finland.
3. Tropical cyclone Idai [12]: affected power stations in Southern Africa and led to cascaded tripping and damage to multiple distribution equipment and let to loss of major substations.
4. Super cyclone Amphan [13]: affected distribution systems, caused widespread flooding of transformers and damage of distribution systems, poles, transmission lines.
5. Cyclone Hudhud [14]: affected the southeast coastline of India and resulted in load reduction.
6. Chinese winter storms [15]: led to large-scale electric power interruptions affecting more than 200 million people.

7. The Texas snowstorm [16]: brought unprecedented cold temperatures and heavy snowfall, leading to widespread power outages and infrastructure challenges across the state.
8. California wildfires [17]: caused extensive damage to electric distribution systems, leading to widespread outages and challenges in restoring electricity to affected areas.
9. Australian bushfires [18]: impacted electric distribution networks, resulting in service disruptions and infrastructure damage as flames engulfed distribution lines and equipment.

Aside from weather-related threats, threats to distribution system resilience stem from possible cyber attacks [19, 20]. The growing use of smart devices in electric distribution networks increases the vulnerability to cyber attacks, as these devices introduce new attack surfaces and potential vulnerabilities. Attackers can exploit weaknesses in communication protocols, sensors, actuators, and associated software.

For example, the recent cyberattacks on Ukrainian power grid have caused millions of people to lose power. To assess the impact of both weather-related and cyber events on distribution systems, cyber-physical distribution system resilience needs to be quantified using extensive analysis and evaluation methodologies [21, 22]. This will enable operators and planners to identify vulnerabilities, prioritize mitigation efforts, and develop more effective defense strategies.

2 Grid Resilience and Metrics

2.1 Defining Grid Resilience

Electricity is the foundation on which every sector of a country's economy operates. This utility plays a critical role in healthcare delivery, education, transport, effective communication, military defense, etc., so a disruption in the electrical infrastructure is effectively an attack on national economy and security. Because of its outdated infrastructure, the electric grid is becoming increasingly vulnerable and unprepared to deal with a variety of *extreme events* that threaten normal and expected system operation.

Definition 1 An extreme event (used interchangeably with grid event) is any disruption with a capacity to change the power system's normal operation.

As highlighted in Sect. 1.2, the last decade has seen an increase in the number of extreme events, driven largely by rising global temperatures and other climatic changes [23]. In February 2021, a winter storm produced a huge electrical generation failure in Texas, resulting in power outages affecting nearly 4.5 million residents. The outages resulted in at least fifty-seven (57) deaths and more than \$195 billion in property damage, drawing attention to the energy system crisis and its potential causes [24, 25].

Another source of extreme events that has seen an increase in activity is the cyber domain. This consist of grid events like physical attacks, operator error, equipment failure and cyberattacks. In 2016, Russian intelligence agencies targeted US government agencies, like Burlington Electric, in a series of cyberattacks dubbed "Grizzly Steppe", exposing a vulnerability of the nation's grid to cyberattacks [26]. In December 2015, alleged Russian hackers executed the Sandworm cyberattack on the Ukrainian power grid, resulting in a six-hour outage for about 230,000 residents in western Ukraine [27]. This was

the first publicly reported successful cyberattack against a power grid.

Even though hackers failed to disrupt the US electric grid in the Grizzly Steppe attacks, there is still evidence that the growing internet of things world poses a potential vulnerability to the power grid, so there is a critical need for a robust and flexible power system that will be resistant to future threats.

The concept of resilience is multidimensional, and it is crucial to the robustness and adaptation of electric distribution networks in the face of disruptions. Several working definitions of resilience have been proposed by research institutions and grid stakeholders. However, at their core, these nuanced definitions share a common theme, emphasizing the grid's ability to prepare for, withstand, and recover from disruptions. Common definitions for electric distribution system resilience include:

Definition 2 According to the Department of Homeland Security (DHS), *resilience* is the ability of a system to adapt to changing conditions and withstand and rapidly recover from disruption [28].

Definition 3 According to the North American Energy Resilience Model (NAERM), the DOE defines *resilience* as the ability of a power system and its components to withstand and adapt to disruptions and rapidly recover from them [29].

Definition 4 The National Renewable Energy Laboratory (NREL) defines *resilience* as a system's ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions through sustainable, adaptable, and holistic planning and technical solutions [30].

Definition 5 The IEEE Technical Report PES-TR65 and FERC Docket No. AD18-7-000 defines *resilience* as the ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event [31].

Connecting the core idea of resilience from the various definitions, this work defines resilience for distribution systems as *“the ability of the grid to anticipate an extreme event, withstand the the extreme event while maintaining operational integrity, and recover quickly while minimizing downtime.”*

2.2 Resilience Versus Reliability

Power system reliability and power system resilience are related but distinct concepts. Conceptually, resilience pertains to the power system response to extreme events that rarely occur but have high impact on system operations. Reliability relates to normal events with increased frequency of occurrence but have relatively little impact, including outages and disturbances under routine operating conditions [32]. Reliability and resilience are related in the following way: resilience is a system attribute, and reliability is a system performance metric. In many scenarios, increased reliability leads to greater resilience. For instance, investing in hurricane-resistant system hardening boosts reliability. However, in other scenarios, a reliable system could have lower resilience. For example, reclosing power lines may incorporate monitoring and automatic fault detection techniques that improve reliability, however, during the fire season, they increase the fire risks and cause cascading failures, which reduce resilience [33].

Regarding their enabling factors, Sandia National Laboratory points out that reliability metrics are not cause-specific, while resilience metrics are [34]. It also points out that the available reliability metrics address the grid's capability to deliver power under normal operating conditions, and not how the grid responds to disruption. Thus, there is an essential need for resilience evaluation methods to bridge the gap.

2.3 Resilience Evaluation

Evaluating the resilience of electric distribution systems is critical for assured electricity delivery in the face of grid events. This evaluation can be qualitative, focusing on attributes like redundancy and automation, or quantitative, employing simulations and metrics to assess how long a system can function after a disturbance. Graphically, power system resilience can be evaluated using resilience curves used to represent the performance of a power grid to an extreme event. By incorporating resilience evaluation into planning and operation, the power grid can become more robust and flexible, with minimal casualties to critical loads.

2.3.1 Resilience Curves

In power system applications, assessing the performance in response to a grid event enables us to identify the temporal phases of the power system's resilience. Given that the graph evaluates system performance over time, the horizontal axis represents time and the vertical axis represents the performance of the system, which can be understood by a variety of relevant factors. These factors include the availability of critical services, the number of loads supplied, or the economic performance. Resilience triangles and trapezoids are two ways to visualize resilience curves.

The resilience triangle was introduced and first applied to evaluate community resilience, particularly in the context of seismic events and natural disasters such as earthquakes and hurricanes. It plots the quality of infrastructure against time and uses the area of a triangle representing system performance to assess the loss of resilience during a specific event. The resilience triangle was used to evaluate the resilience of the electric distribution system in Louisiana following Hurricane Katrina [35].

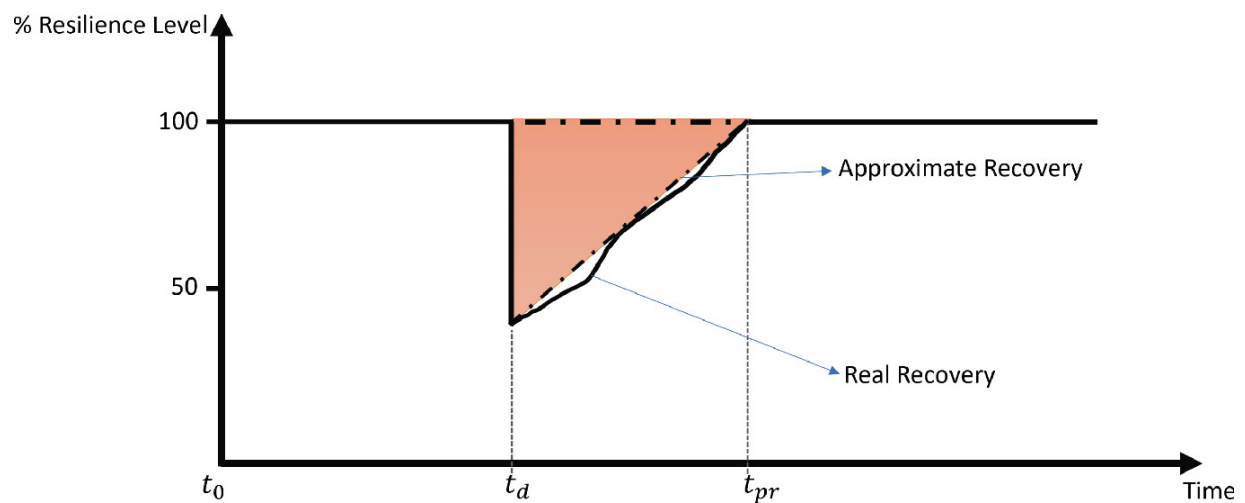


Fig. 2 Resilience triangle

However, the resilience triangle is limited in its ability to capture the complexities of network performance decline and recovery, particularly in the context of weather-related disasters like hurricanes and windstorms. Figure 2 displays the image of a resilience triangle. It conveys a quick and instantaneous drop in network performance, which is typical of earthquakes but not typically applicable to weather-related events, given that deterioration occurs gradually over time. In addition, this resilience curve makes the unrealistic assumption of immediately launching network restoration, which is impossible due to the requirement for logistical planning and the deployment of repair teams and spares. Thus, the need for an additional

resilience curve with a nuanced approach to assessing resilience in different disaster scenarios.

The resilience trapezoid tackles the limitations of the resilience triangle by addressing how resilience indicators evolve across five stages, each signifying a unique phase of a system's resilience to an event: preventative actions (pre-disturbance state), deterioration (disturbance progress), network reconfiguration (post-disturbance), restoration (restorative), and infrastructure recovery (post restorative state). Thus, this curve provides an improved understanding of resilience dynamics, taking into consideration different stages of network performance and recovery processes.

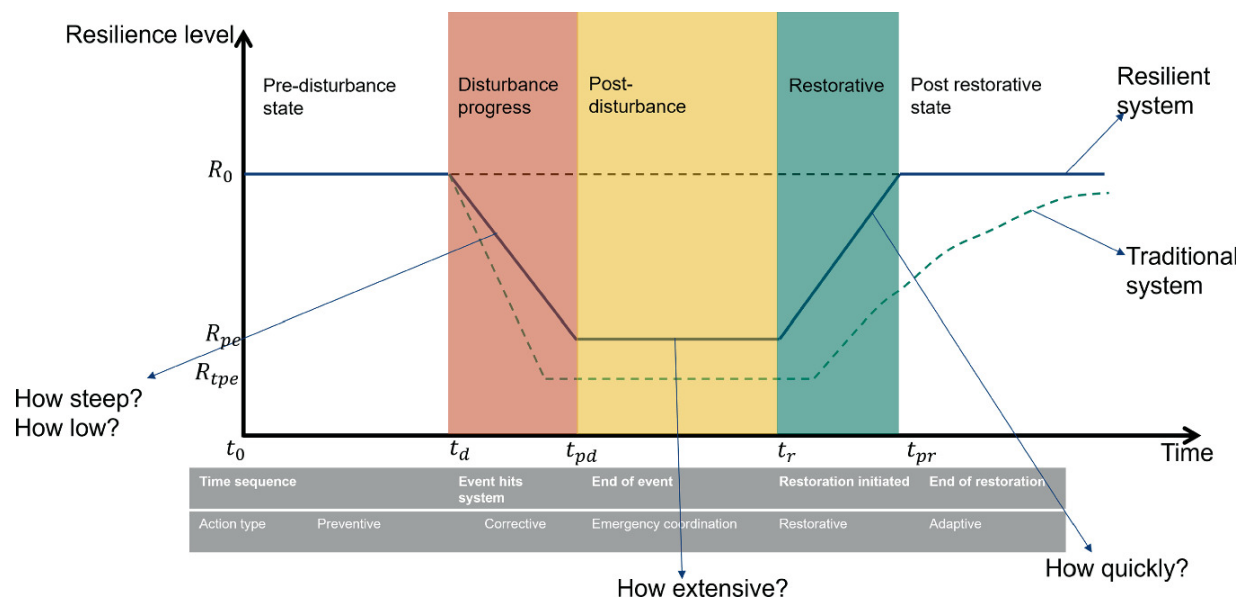


Fig. 3 Resilience trapezoid comparing the resilience of a resilient system to that of a traditional system

The resilience trapezoid accommodates for pre-restoration delays that prevent recovery work from commencing immediately owing to safety concerns. Figure 3 uses the resilience trapezoid to compare the resilience of a resilient system to a traditional or non-resilient system. The curve depicts these delays with a flat bottom, which

represents the time period when healing processes are postponed.

2.3.2 Resilience Metrics

This section defines resilience metrics as “*frameworks to assess the level of resilience of a distribution system, typically following an extreme event.*” Defining a metric for resilience represents the initial step in a resilience assessment process to identify vulnerabilities in the network and take measures to elevate the resilience of the network. These metrics evaluate various aspects such as robustness, adaptability, redundancy, flexibility, and response to grid events. However, in some cases, performance indicators go beyond technical aspects and assess social welfare [36]. Resilience metrics are broadly classified as qualitative and quantitative.

Qualitative metrics are attribute-based metrics, and are useful for long-term planning and decision making. They provide insights into the influence of auxiliary infrastructures and services, which may be overlooked in quantitative assessments. However, they lack numerical descriptors, making them prone to errors [35]. They are generally divided into two sub-categories: (i) conceptual frameworks that assess resilience based on criteria and guiding principles, and (ii) semi-quantitative indices that normalizes resilience-based system characteristics on a Likert scale or as a percentage.

Quantitative resilience metrics are performance-based metrics that provide numerical estimates to quantify the resilience of a system. Thus, they provide a comparable method for evaluating grid resilience under different operating conditions. Due to the absence of a standardized classification for quantitative metrics, which is influenced by factors such as the type of system, operating conditions, and the extent of disruption damage, various classifications

attempts for quantitative metrics exist. Resilience metrics were divided into three categories by ref. [37]: (1) resilience metrics derived from resilience curves, (2) resilience metrics based on system pre- and post-disruption performances, and (3) resilience metrics derived from system reliability and restoration. Ref. [35] grouped quantitative metrics into (1) analytical, where metrics are grouped based on their perceived performance, (2) probabilistic, using probability indices (3) curve-based metrics, derived from the resilience curve and (4) reliability-based metrics, using reliability indices to quantify resilience. Additionally, quantitative resilience metrics were grouped by [38] into six main categories: (1) according to the load recovered or the energy not supplied, (2) according to the supplied critical loads during the disruption, (3) according to the curve analysis, (4) according to modified reliability metrics, (5) according to graph theory, and (6) according to the costs incurred due to the disruption.

The application of a type of resilience metric depends on factors such as the specific objectives, regulatory requirements, and operational considerations like the voltage level of the power system. While generation and transmission systems can encounter challenges during severe weather events or natural disasters, it's often the distribution network that experiences the most significant disruptions, since it lies at the edge of the grid with many components across a wide geographical span. For instance, in 2005, Hurricane Katrina severely impacted distribution networks in the Gulf Coast region of the United States, leaving millions without power for weeks due to widespread damage to local distribution infrastructure such as poles, transformers, and substations [39]. The extensive reach and vulnerability of distribution systems to localized damage underscores the critical need for robust

infrastructure and disaster preparedness measures at this level.

2.4 Resilience Metrics for Distribution Systems

This section discusses resilience metrics that have been developed to evaluate electric distribution systems. Even though a metric can fit into more than compartment, the metrics discussed are categorized into five categories according to their derivation technique: topological, curve-based, probabilistic, reliability-based, and cost-based metrics (Fig. 4).

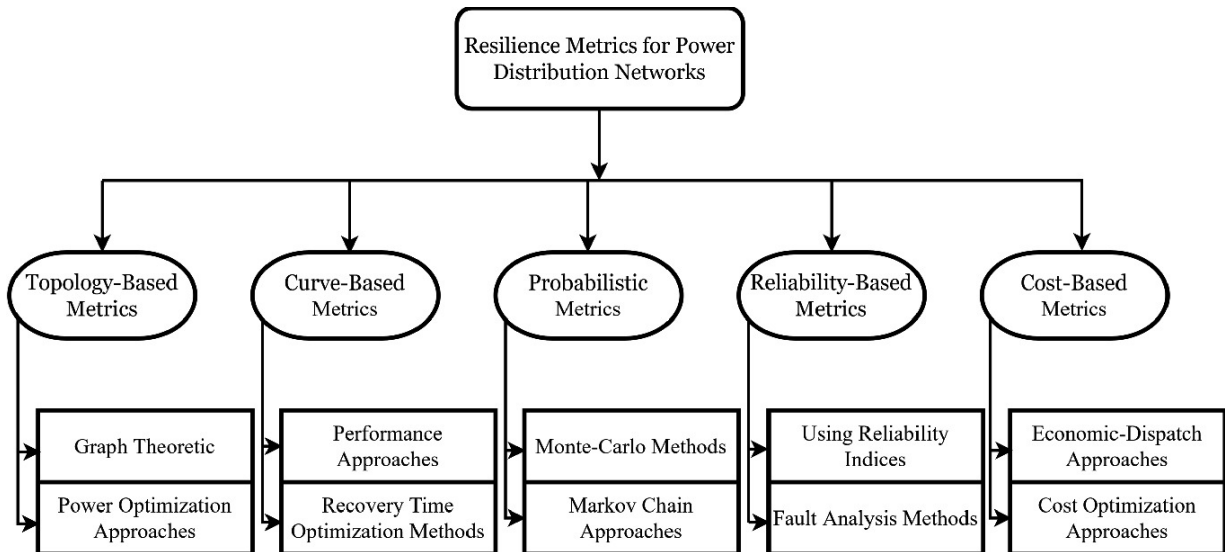


Fig. 4 Classification of resilience metrics for distribution systems

2.4.1 Topology-Based Metrics

Topology-based power metrics are measures used to evaluate the performance of an electric distribution system based on its topology. It makes use of optimization techniques, graph theory, and decision theories to evaluate power system performance under disruption. In [40], analytical hierarchical process (AHP) and percolation theory were used to quantify the resilience of an electric distribution system. The resilience of each distribution system configuration is added together to calculate the

system's overall resilience, with power flow feasibility as the most vital element. The total resilience $\mathcal{R}_{total}$ is mathematically defined as shown in Eq. 1:

$$\mathcal{R}_{total} = v + (1 - v) \sum_{i=1}^{n-1} w_i \cdot \mathcal{R}_i \quad (1)$$

where $\mathcal{R}_{total} = [\mathcal{R}_1, \mathcal{R}_2, \mathcal{R}_3, \dots, \mathcal{R}_n]$ represents a vector made up of resilience values for n viable configurations of the distribution network, while w_i denotes the normalized weights allocated to resilient configurations, $v = \max[\mathcal{R}_1, \mathcal{R}_2, \mathcal{R}_3, \dots, \mathcal{R}_n]$, and $\mathcal{R}_i$ is made up of vectors ordered in ascending order and includes composite resilience ratings for networks that have not attained the maximum resilience. The increasing total resilience score indicates a larger number of channels connecting functional components to critical loads.

The authors of [41] proposed a metric to identify the most resilient pathways for restoring critical loads, considering all potential contingencies that could occur within a distribution network. The metric, based on graph theory and choquet integral, takes seven network values as input criteria, and the weights and interaction indices as parameters of the model to determine the importance of each criterion. An array of all possible paths for any loss-of-source scenario is ordered by priority, and paths are selected optimally to enhance the resilience of the electric distribution system.

Pandey et al. [42] developed a topology-based resilience index to minimize the impact of uncontrolled islanding on system using processed synchrophasor data. The challenge was solved through iterative reconfiguration of the network, which included moving critical loads and shedding non-critical loads in response to a grid event. The reconfiguration algorithm is carried out as a spanning tree

optimization algorithm, maximizing the number of critical loads supplied. The resilience metric R_i was defined as:

$$R_i = \frac{w_1 \cdot bc_i}{w_2 \cdot \frac{l_{g,i}}{l_{max}}} \times \frac{P_{critical}}{P_i}, \quad (2)$$

where w_1 and w_2 are system-specific weights, bc_i refers to the betweenness centrality of corresponding node i , $l_{g,i}$ denotes the shortest path between a node and a generator, whereas l_{max} stands for the maximum path length in a given network. $P_{critical}$ and P_i indicate the real power requirements of critical loads and all loads, respectively, at the evaluated node and downstream.

2.4.2 Curve-Based Metrics

Curve-based metrics assess a power system's resilience by analyzing characteristic curves that show system performance under various conditions. Based on the resilience curve, curve-based measurements split system performance into five categories: performance before interruption, performance during disruption, length of disruption, recovery speed, and recovery status. Panteli et al. [43] introduced the $\Phi\Lambda E\Pi$ (pronounced "FLEP") resilience metrics as multi-phase resilience metric based on the resilience trapezoid. This metric is comprises four independent metrics $\Phi\Lambda E\Pi$, and an *area* metric which is dependent on the $\Phi\Lambda E\Pi$ metrics. Φ determines how fast the system resilience drops, Λ determines how low the resilience drops, E represents how extensive nature of the disruptive period, and Π represents the speed of recovery. Additionally, the area of the curve is taken expressed as the integral of the trapezoid. The metrics are mathematically represented as:

$$\begin{aligned}
\Phi &= \frac{P_{pd}-P_0}{t_{pd}-t_d} \\
\Lambda &= P_0 - P_{pd} \\
E &= t_r - t_{pd} \\
\Pi &= \frac{P_0-P_{pd}}{t_{pr}-t_{pd}} \\
Area &= \int_{t_d}^{t_{pr}} P(t)dt
\end{aligned} \tag{3}$$

where P represents system performance P_0 represents initial performance, P_{pd} represents performance post destruction. In [44], a two-stage non-linear optimization formulation is outlined to model post-hurricane resilience in distribution systems, using microgrids to improve the resilience. Bat algorithm is implemented to handle the discrete and nonlinear characteristics of the formulation. The post-disruption objective minimizes the time slots required for load restoration, mathematically defined as:

$$R = \gamma \int_{t_r}^{t_r+T^{sw}} \left(\sum_l \omega_{l,t} \cdot P_{l,t}^d \right) dt - G, \forall l \in Q, \tag{4}$$

where G denotes the costs associated with distributed energy resources, γ is a conversion factor used to translate system performance into a monetary value. Q represents the set of branches (denoted as l) connected to a bus linked to node n . ω_l represents the weighting factor of bus l , and $P_{l,t}^d$ indicates the total load demand on bus l .

2.4.3 Probabilistic Metrics

Probabilistic metrics incorporate probabilistic models to analyze the stochastic nature of disruptive events and their impact on power system performance. By quantifying the probability of different outcomes, utilities can prioritize resilience-enhancing measures, allocate resources effectively, and develop strategies to mitigate risks and improve system resilience. These metrics utilize stochastic

optimization approaches such as chance-constrained optimization, and probabilistic risk assessment methods like Monte Carlo simulations to assess resilience.

Luo et al. [45] proposed a framework to assess the resilience of electric distribution networks based on the impact of critical loads during extreme weather events. The Monte Carlo approach is utilized to simulate the entire sequence of events for a fault scenario during an extreme weather event. Load levels are assigned varying weights based on their relevance, and the weighted loss of load is used to evaluate resilience. The distribution network's resilience index R is determined as:

$$R = \frac{1}{\int_{t_0}^t \left(\frac{\frac{1}{M} \sum_{s=1}^M \Delta p(X_i)}{P(t_0)} \right) dt}, \quad (5)$$

$$\Delta p(X_i) = 6 \cdot \Delta p_1(X_i) + 3 \cdot \Delta p_2(X_i) + 1 \cdot \Delta p_3(X_i)$$

where $\Delta P(X_i)$ represents the overall critical load loss in the scenario, and M is the number of samples taken. In [46], an analytical framework is developed to address the extensive disruption and the restoration of power distribution following a severe weather. This metric integrates non-stationary failure and recovery random processes with network configurations to generate a dynamic and probabilistic measure for evaluating distribution system resilience. The network resilience determined to be:

$$R = 1 - \frac{1}{J} \int_{t_e=0}^t \left(\sum_{s=f,o} \sum_{z \in Z} \lambda_z^{(s)}(t_e) \times P_r \left\{ D_z^{(s)}(t_e) > k \right\} \right) dt_e \quad (6)$$

where the second term of the Eq. 6 corresponds to the anticipated percentage of aging recoveries at time t , $k = (t - t_e + d)$ and s specifies the three failure scenarios. $\lambda_z^{(s)}(t_e)$ represents the likelihood of a scenario occurring within the period, where $(t_e - dt_e, t_e]$, z refers to a subset of

the network located in region Z , and $P_r\{D_z^{(s)}(t_e) > k\}$ indicates the probability of failures lasting longer than k [47].

2.4.4 Reliability-Based Metrics

Reliability-based resilience metrics assess the resilience of a power system by focusing on its ability to maintain reliable operation under various conditions, including normal operation conditions and adverse grid events. These metrics employ resilience indices and fault analysis methods to quantify the resilience and reliable performance of the power system under disruption. In [48], a metric for resilience based on the reliability theory concept of availability is developed to quantify the resilience of critical infrastructure. Availability is utilized as a suitable measure of resilience through the dependence on the Mean Up Time (MUT) and Mean Down Time (MDT), since the resistance to disruption increases the MUT, and the speed of recovery reduces the smaller MDT. Thus the resilience was defined as:

$$R = 1 - U_{N/S}e^{-\mu T_s}, \quad (7)$$

where $U_{N/S}$ denotes the unavailability in the absence of storage, T_s stands for the storage capacity, and μ denotes the total repair rates associated with a direct transition from a failed state to an immediate operational state of the system. Ref. [49] introduced a framework for assessing electric distribution system resilience based on risk-based metrics, making use of Value-at-risk (VaR_α) and conditional-value-at risk ($CVaR_\alpha$). $CVaR_\alpha$ quantifies operational resilience by calculating the estimated loss from grid events that surpass a pre-specified risk limit, α . The resilience was expressed mathematically as:

$$R = (1 - \alpha)^{-1} \int_{U(I) \geq V_{aR\alpha}} U(I)p(I)dI, \quad (8)$$

where $U(I)$ represents the system performance loss and $p(I)$ represents the probability of event occurrence.

2.4.5 Cost-Based Metrics

Cost-based metrics assess the resilience of a power system by considering the economic costs associated with grid events. These metrics utilize economic dispatch and cost optimization techniques to quantify the financial impacts of disruptive events, such as downtime costs, restoration expenses, and customer losses.

In ref. [50], energy hubs are utilized to demonstrate how energy resources interact in microgrids. Additionally, multi-energy carrier microgrid operational costs during power supply outages are examined. The resilience index r is derived as the exponential of the negative ratio between disruption-induced operational costs of multi-energy carrier microgrids and the budget of the attacker causing the disruptions.

$$R = e^{-\left(\frac{\gamma - \gamma_0}{M}\right)} \quad (9)$$

where, γ and γ_0 are operational costs of disrupted and non-disrupted multi-energy carrier microgrid. As a result, a low resilience score implies that the multi-energy carrier microgrid is extremely susceptible to disruptions. Ref. [51] proposed integrating transportable energy storage systems (TESS) into distribution networks for cost-effective post-disaster restoration. Resilience was defined as a mixed-integer linear program to estimate a TESS scheduling sequence that minimizes customer interruption, microgrid generation, TESS transportation, and battery maintenance costs.

Even though resilience metrics may be derived from multiple domains, new threats that arise, like cyberattacks or extreme weather occurrences with little to no historical data, may limit their use to analyze the distribution grid. This is because existing resilience metrics have limitations, including (1) a heavy dependence on system and historical data, which may be insufficient or unreliable, (2) a single-dimensional focus, which makes a metric for one distribution system inapplicable to another, and (3) a static nature that does not account for evolving threats, vulnerabilities, and system conditions.

As an example of this failure to consider resilience during the event, consider the 2021 Texas blackouts. The Texas grid's focus on guaranteeing robustness and resourcefulness led to unrealistic performance expectations, which failed due to inadequate situational awareness of the challenges it faced. We propose the adaptive resilience framework in Sect. 4 to tackle the dynamic and complex nature of resilience in electric distribution systems.

2.5 Resilience Taxonomy

In Sect. 2.4, we established that the concept of resilience is multidimensional and varies according to the specific domain of application. The taxonomy of power system resilience makes it possible to categorize the various dimensions of resilience to assess specific vulnerabilities and build a more robust and adaptive electrical grid. This work builds upon the work of [52] to develop six dimensions to categorize resilience, based on event type, event time frame, voltage level, resilience approach, resilience domain, and recovery type.

Table 1 The taxonomy of resilience

Applications	Advantages	Limitations
By time horizon		
<i>Infrastructural resilience</i>		
• Protecting critical infrastructure from cyber threats • Upgrading aging infrastructure and integrating advanced technologies • Grid resistance to extreme weather events	• Continuity of supply to critical loads • Provides long term value and a return on investment • No planning computation required	• Resources may be quickly depleted • Limited to environmental and ethical considerations • Dependent on unknown future conditions like population and threats
<i>Operational resilience</i>		
• Critical facilities with known load priorities • Asset management and maintenance optimization • Emergency response and restoration • Cybersecurity incident response	• Sustainability of resources for maximum time possible • Interruptions due to outages are not experienced by mission-critical facilities	• Loss of multiple non-priority loads • Advanced planning and computation required • Susceptible to cyber-attacks
By event type		
<i>Natural events</i>		
• Hurricanes • Wildfires • Earthquakes	• Reduced downtime due to natural disasters • Protection of grid assets • Enhanced grid reliability	• Protection against one type of event does not apply to other events • Limited scope of mitigation • Constrained by costs and resources
<i>Cyber events</i>		
• Cyber-attacks • Equipment failure	• Reduced risk of disruption • Improved incident response • Offers smooth adaptability to emerging threats	• Dependence on advanced technologies • Susceptibility to human errors

Applications	Advantages	Limitations
By voltage level		
<i>Distribution system resilience</i>		
• Flexible energy storage • Advanced restoration algorithms • Improved outage management systems • Microgrid formation capability	• Improved resilience leads to higher reliability indices • Reduced maintenance costs	• Business-case is hard to arrive at due HILF nature of the events • Limited redundancy of interconnected networks
<i>Transmission system resilience</i>		
• Vulnerability analysis • Higher than N-2 contingency tools	• Improved voltage stability • Greater leverage of restructured grid policies	• Cost-intensive for implementation • Computation costs are very high due to large number of nodes
By approach		
<i>Proactive resilience</i>		
• Strategic position of crews in anticipation of damage • Microgrid formation and stable operation	• Higher reliability • Better maintenance of utility owned infrastructure	• Conservative approach • Cost-intensive
<i>Reactive resilience</i>		
• Rapid damage assessment • Grid reconfiguration	• Allocates resources to expedite recovery • Provides adaptability to dynamic threats	• Limited effectiveness, since it depends on the impact of the extreme event • Susceptible to future events because of the lack of learning from past events
By domain		
<i>Cyber-physical system resilience</i>		
• Regular security upgrades	• Defense against cyber attacks and cyber bullying	• Not attack proof as adversaries can find new mechanisms

Applications	Advantages	Limitations
• Monitoring of network traffic • Encryption	• Improved communication over system components and greater visibility	• Improved cyber-system resilience may not detect past dormant malware installed
<i>Economic resilience</i>		
• Charging customers a nominal fee in high-risk areas • Participation in energy markets	• Finances better maintenance of grid • Inventory is ready in preparation of event	• Dependence on consumer cooperation • Chances of overstocking of inventory and cash reserves
<i>Social resilience</i>		
• Community-based energy initiatives • Crisis communication and engagement • Social networks and support systems	• Reduced vulnerability to extreme events • Cost effective	• Limited coordination and cooperation • Uneven distribution of resources to different socioeconomic groups
By recovery type		
<i>Structural resilience</i>		
• Hardened power plants • Resilient substation design • Robust transmission towers and poles • Flood mitigation measures	• System is restored to its original structure after event • Reduced downtime	• Higher initial cost • Some measures may have adverse environment impacts
<i>Functional resilience</i>		
• Emergency backup systems • Remote monitoring and control • Load shedding programs • Emergency communication	• System functionality is maintained even though structure could be different • Risk mitigation to natural and cyber events	• Dependence on customer cooperation • Costly to implement • Limited capacity to withstand prolonged outages
<i>Adaptive resilience</i>		

Applications	Advantages	Limitations
• Dynamic grid operations • Scenario planning and risk assessment • Continuous learning and improvement	• Applicable to systems with limited known data • Provides an improved recovery from emergencies and disruptions • Reduce downtime from disruptions and saves costs	• A technologically advanced form of P.S. resilience • Potential interoperability issues from integrating technologies within power systems

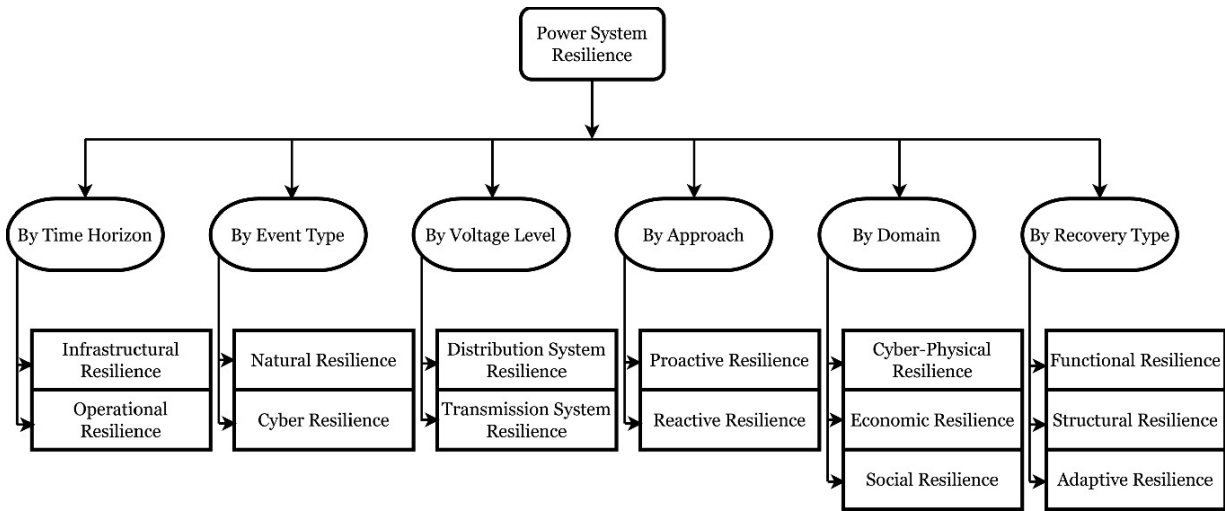


Fig. 5 Taxonomy of resilience

Resilience can be explored along the interconnected dimensions of economics and engineering. Economics of resilience measures the financial impact of disruptions on the community, and resilience in the context of engineering explores resilience from various points in time (pre-, during, and post-event) or considers the nature of the attack itself (“resilient to what?”) [52]. The various categories of resilience are broken down as follows:

1. In distribution systems, *infrastructural* resilience focuses on the robustness and integrity of the physical components and structures of the network to meet a grid event, whereas *operational* resilience focuses on

the ability to maintain essential functions and adaptability in response to the grid events.

2. In distribution systems, *natural* resilience focuses on the grids ability to withstand disruptions from all events that are natural in occurrence, *cyber* resilience focuses on the system's capacity to defend against and recover from grid events that arise as the result of human and animal influence.
3. A distribution system exhibits *proactive* resilience when it uses pre-emptive strategies and measures to prevent or mitigate possible disruptions, it exhibits *reactive* resilience when it focuses on responding to disruptions after they occur, with emphasis on rapid recovery and adaptation.
4. A distribution system exhibits *functional or service* resilience if it has the capacity to sustain important operations and services despite disruptions to swiftly repair damaged elements of the distribution network to assist consumers during outage recovery.
5. An electric distribution system is said to be *structural resilient* if it has the physical infrastructure to endure and adapt to different disruptions while sustaining critical operations and services.
6. A distribution system exhibits *adaptive* resilience if it has the ability to dynamically adjust and evolve in response to changing conditions and threats. This involves continuously monitoring the system, identifying vulnerabilities based on past events and patterns, and implementing adaptive strategies to enhance reliability and maintain operational stability.

The taxonomy of resilience enhances our understanding of resilience in power systems. This allows stakeholders

from many sectors to better communicate about power systems, resulting in more efficient cooperation and decision-making. In effect, it provides the needed support in establishing conceptual and computational tools to drive ongoing resilience-based initiatives and improve current resilience metrics. In the next section, we discuss the adaptive resilience metrics, which provide the performance evaluation needed to achieve adaptive resilience.

3 Adaptive Resilience Metric

Adaptive resilience metrics are dynamic, context-aware techniques that continuously monitor, analyze, and adjust the resilience outlook in response to changing system circumstances and evolving threats. These metrics recognize that electric distribution systems operate in complex and uncertain environments, where disruptions, hazards, and vulnerabilities can vary over time.

By incorporating new information, updating risk assessments, and adjusting resilience measures dynamically, adaptive resilience metrics enable grid operators to anticipate and respond effectively to emerging challenges and uncertainties.

Figure 6 displays the framework to incorporate adaptive resilience in power systems. Adapting resilience metrics to grid specific scenarios depends on four main attributes: input data, scenario, event type and user information. To effectively adapt resilience metrics to each use case, grid data from a variety of sources are initially collected to ensure that the metrics represent current conditions. Next, a scenario analysis must be performed to adjust the resilience to the grid situation under consideration. The particular event must be accommodated because each extreme event has a different consequence on the grid. Finally, the grid operator should incorporate relevant grid metric information into the adaptive metric formulation.

1. **Input Data:** Input data refers to specific information the metric will be used to assess resilience. This includes a variety of data points essential for assessing and enhancing resilience:
 - System configuration data: network topology, redundancy levels.
 - Operational data: real-time load data, voltage levels, frequency metrics.
 - Environmental data: pattern of weather conditions and climate data, temperature.
 - Performance metrics: maintenance data, system reliability indices.
2. **Grid Scenario:** This refers to the overall situation or condition of the grid you are assessing. Some examples include:
 - Weak Grid: Vulnerable to cascading outages due to limited redundancy.
 - Aging Grid: Increased likelihood of equipment failure due to outdated infrastructure
 - Highly Distributed Generation: Potential challenges with managing intermittent renewable energy sources.
 - Grid with increased integration of smart devices.
 - Urban or rural grid: differences in load density and infrastructure development.
3. **Event Type:** Event types are specific disturbances or disruptions that the grid might face. A checklist of common event types includes:
 - Events occurring from the natural domain: including hurricanes, wildfires, snowstorms, earthquakes, tornadoes, etc.

- Events occurring from the cyber domain or because of man-made influence: including cyberattacks, physical attacks, equipment failure, human errors.
4. User/Operator Information: This refers to information or grid data that is readily available to the grid operator. Available grid information includes real-time monitoring data, historical data records and predictive analytics.

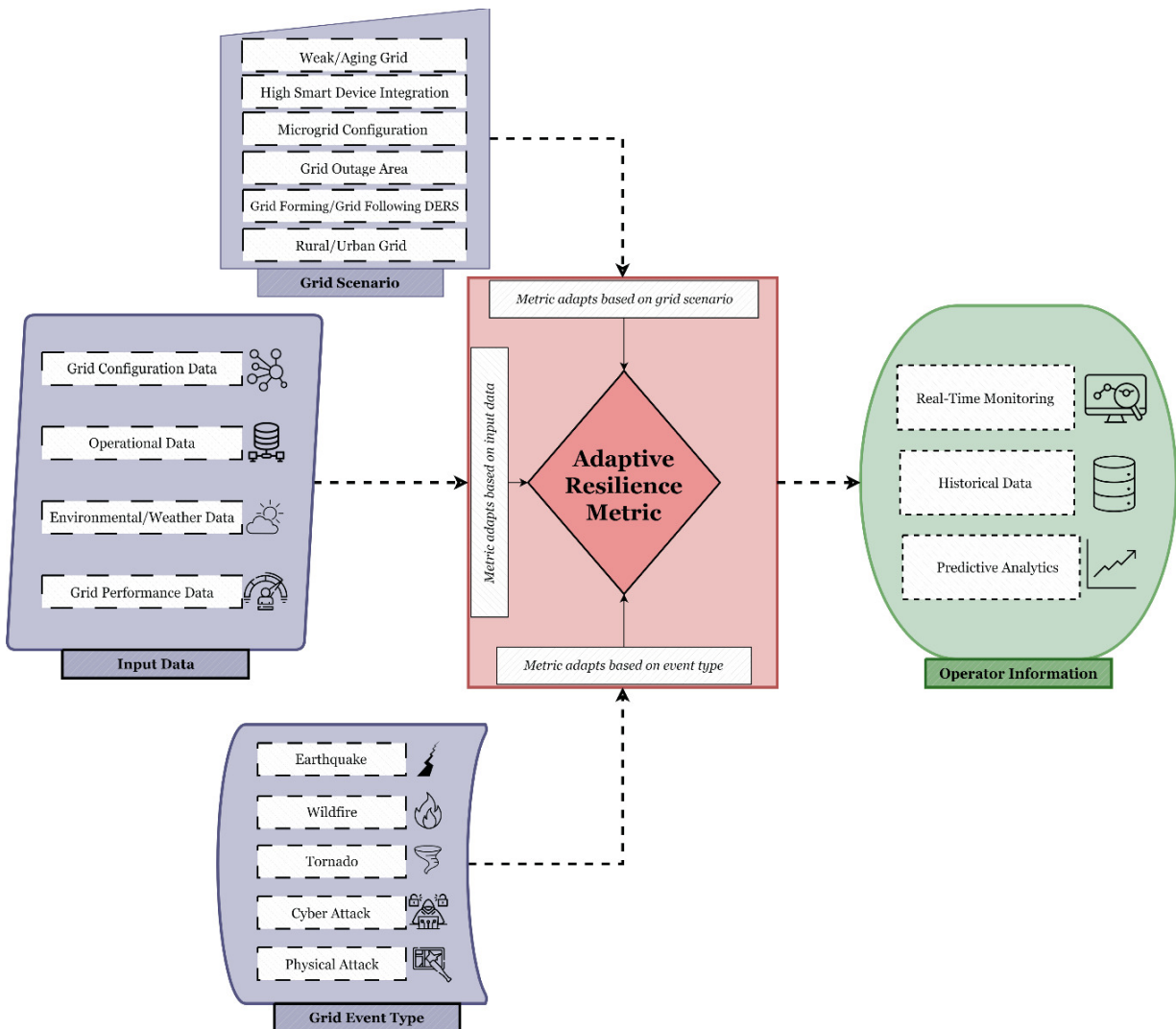


Fig. 6 Framework for adaptive resilience metrics

3.1 AWR: Anticipate, Withstand, and Recover Metrics

The Anticipate, Withstand, and Recover (AWR) metric is a type of resilience metric that factors the changing system characteristics throughout the progression of an extreme event. This section outlines the development of the AWR Metric [53] as a multitemporal framework that integrates three distinct metrics: anticipate, withstand, and restore metrics, based on relevant factors developed using theoretical concepts from the national emergency preparedness paradigm, graph theory, power engineering, and multi-criteria decision making (MCDM). At each stage of event progression, the metric employed is that which captures the central property of resilience most relevant to that stage.

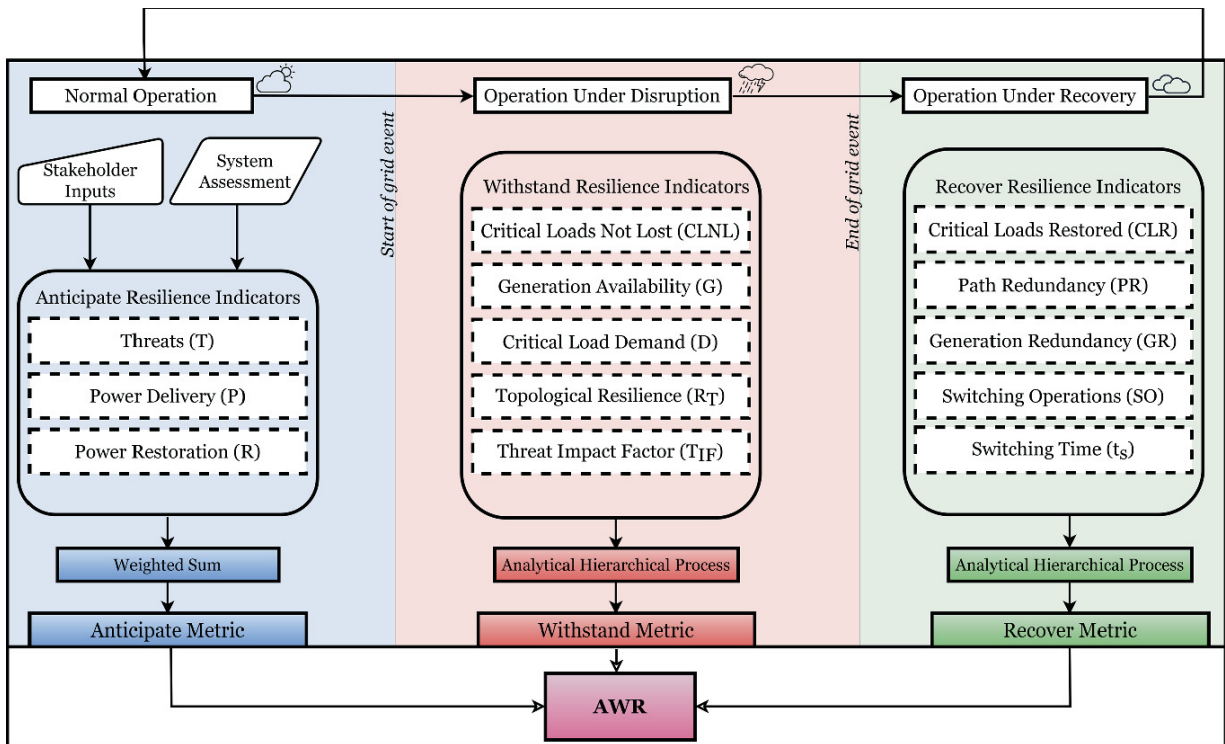


Fig. 7 Framework to compute AWR metrics

Figure 7 displays the overview of the AWR metric formulation. Before a grid event, a system benefits from

situational awareness, enhanced readiness, and predictive features that warn the operator of an upcoming event. During the event, the system's resilience hinges on its ability to withstand and absorb the impact. After the event, the system's resilience is derived from a successful recovery and a return to normal functioning. The formulation of the AWR Resilience Metric involves several key components. To enable resilience, a distribution utility adopts measures in the form of infrastructure hardening (e.g., using underground conductors), situational awareness (e.g., using better threat sensing mechanisms), redundancy, and resource allocation (e.g., creating alternative electric paths), collectively known as resilience planning investments (RPI). Once the RPIs are available, three resilience metrics ($\mathfrak{R}_A$, $\mathfrak{R}_W$, and $\mathfrak{R}_R$) are used to determine the best combination through the evaluation phase, based on threat and vulnerability assessment.

3.1.1 Anticipate Metrics Formulation

To quantify *anticipate* resilience, static factors from key domains of physical resilience—threat and vulnerability, power delivery and loads, and restoration and recovery—are considered. Each factor is assigned a maximum score, and the resilience is calculated as the ratio of the actual response to the maximum response. For each threat, the *anticipate* metric score is a weighted sum given as:

$$\mathfrak{R}_A = \sum_{i=1}^N S_i^T W_i^T + \sum_{i=1}^N S_i^P W_i^P + \sum_{i=1}^N S_i^R W_i^R, \quad (10)$$

where S_i^T and W_i^T denote the score and weight of the vulnerability domain, S_i^P and W_i^P denote the score and weight of the power delivery and loads domain, and S_i^R and W_i^R denote the score and weight of the recovery and restoration domain.

3.1.2 Withstand Metrics Formulation

To quantify the *withstand* resilience, a vector of resilience factors is selected to analyze the system's *withstand* capacity. An Analytical Hierarchical Process (AHP) is used to consolidate the *withstand* resilience score for each RPI scenario. The generation (G) and critical load demand (D) are calculated using the one-line and power flow data. The critical load demand is derived from the daily load profile. To quantify the severity of the weather event, the threat impact factor (T_{IF}) is generated and applied to each of the risk factors present. The topological robustness ($\mathfrak{R}_\tau$) is computed for each scenario. The critical loads not lost $CLNL$ refers to the proportion of critical loads that remain functional during the event, relative to the total number of critical loads within the system. The collection of resilience factors is presented as a vector $\vec{\mathfrak{R}}_W$:

$$\vec{\mathfrak{R}}_W = [CLNL, G, D, \mathfrak{R}_\tau, T_{IF}] \quad (11)$$

Once the factors are assembled, an AHP is performed to obtain the *withstand* resilience score $\mathfrak{R}_W$ for each scenario. The *withstand* metric score is calculated by

$$\mathfrak{R}_W = \sum_{j=1}^N \rho_{i,j} W_i \quad (12)$$

where $\rho_{i,j}$ is a linear transformation of the $n \times n$ pairwise comparison matrix (PCM), which is the matrix of the impact of each of the resilience factors on the system resilience.

3.1.3 Recover Metrics Formulation

The *recover* metrics depend on the quickness of restoration, redundancy of resources and resourcefulness of assets. The post-threat recovery of the system starts with assessing the extent of damage, with an emphasis on

investments to support switching based reconfiguration. The resilience factors employed in assessing recovery metrics consist of generation redundancy (GR) or the available generation, path redundancy (PR) or the quantity of generation-to-critical load pathways, critical load restored (CLR) or the proportion of critical loads restored to the total critical loads, switching operations (SO) or the number of switching configurations necessary for resilience, and switching time (t_S) to achieve a resilient configuration. The collection of resilience factors is presented as a vector $\vec{\mathfrak{R}}_R$:

$$\vec{\mathfrak{R}}_R = [CLR, PR, GR, SO, t_S] \quad (13)$$

The *recover* metric score is calculated by:

$$\mathfrak{R}_R = \sum_{j=1}^N \rho_{i,j} W_i \quad (14)$$

where $\rho_{i,j}$ is a linear transformation of the $n \times n$ PCM, which is the matrix of the impact of each of the resilience factors on the system resilience.

3.2 Cyber-Physical Resilience Metrics

In modern power distribution systems, integrating Internet of Things (IoT) technology enhances efficiency and resilience. Despite the benefits, this integration exposes the network to cyber risks. This section outlines the development of metrics [19] to assess the resilience of these cyber-physical systems, particularly emphasizing their capability to sustain operations under adverse conditions.

The formulation of the Cyber-Physical Resilience Metric involves several key components:

- **IoT Trustability Score (ITS):** a neural network-based evaluation considering IoT vulnerabilities and their

impact on the system's resilience. Federated learning is employed to enhance privacy and data integrity.

- **Primary-Level Node Resilience (PLNR)**: aggregates individual node resilience, factoring in *ITS* and other critical aspects like network topology and DERs.
- **Distribution System Resilience (DSR)**: a comprehensive metric that combines *PNLR* scores across the system, using game-theoretic data envelopment analysis for optimization.

These contributing factors define the cyber-physical metric and provide the scale of resilience with a multi-faceted analysis. The resulting formulated metrics represent an interplay between cyber security, physical infrastructure integrity, and operational flexibility [19].

3.2.1 ITS Formulation

The *ITS* employs federated learning and an autoencoder model for each IoT device's power system and network packet data. Training individual autoencoder models with global weight parameters (W_G) enables the monitoring of data reconstruction errors (*RE*). Based on the maximum (*RE*) value, a tolerance value (T_{err}) is computed that helps in anomaly detection by flagging data points exceeding T_{err} as anomalous.

Non-Anomaly Ratio (*NAR*) and Cumulative Non-Anomaly Ratio (*CNAR*) are calculated to evaluate the device data over time, providing a metric for assessing comparisons between normal and anomalous data points. The *ITS* is computed using:

$$ITS_t = w_t \times NAR_t + w_{t-} \times \frac{CNAR_t}{CNAR_{max}}, \quad (15)$$

where w_t and w_{t-} are weights satisfying $w_t \geq w_{t-}$ and $w_t + w_{t-} = 1$. The overall *ITS* for a primary node with IoT devices is the average of the *ITS* scores from all clients,

offering an aggregated metric of IoT device reliability within the power distribution system.

3.2.2 PLNR Formulation

The resilience of a cyber-power system's primary level node depends on several factors derived from its secondary-level configuration:

- Available generation capacity, including PV and storage.
- Total amount of critical load downstream of the node.
- Connectivity redundancy among critical loads and nodes with power supply.
- Device and communication vulnerabilities, quantified using the Common Vulnerability Scoring System (CVSS).
- IoT Trustability Score (*ITS*) for IoT devices' reliability.

The complex task of evaluating the impact of these factors on resilience is addressed using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP), integrated with a fuzzy rating aggregation method. This approach accommodates expert opinions and controls uncertainties using fuzzy set theory. Factors are compared pairwise using fuzzy numbers, aggregated across multiple experts, and then normalized to derive weights for each factor. The calculation steps include:

1. Aggregate expert ratings to construct a fuzzy pairwise comparison matrix.
2. Calculate the fuzzy geometric mean and fuzzy weight for each factor.
3. Defuzzify weights using the Center-of-Area method and normalize to get the final weights.
4. Apply a weighted product model to compute the *PNLR* for any primary node as:

$$PNLR = \prod_{i=1}^{n_c} (F_i)^{W_i}$$

where n_c is the total number of considered factors for a given category of primary level node, and W_i is the weight assigned to each factor (Fig. 8).

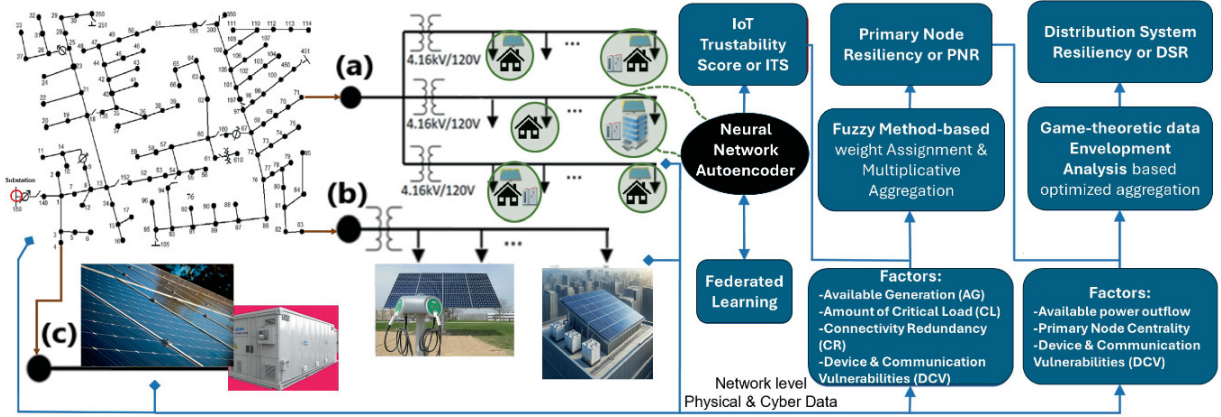


Fig. 8 Overview of the proposed resilience metrics for cyber-power distribution system with IoTs

3.2.3 DSR Formulation

The Distribution System Resilience (*DSR*) metric evaluates the resilience of a power distribution system by considering its primary and secondary-level infrastructure. This metric includes several key factors: Primary Level Node Resilience (*PNLR*), which reflects the secondary level's configuration; Available Power Outflow (*APO*), representing the balance of power after critical loads are accounted for; and Primary Node Centrality (*PNC*), indicating the importance of a node based on its connections, determined through leverage centrality. Additionally, the metric considers the system's vulnerabilities at the primary network (*DCVP*) by using the Common Vulnerabilities and Exposures (*CVE*) standards and the National Vulnerability Database (*NVD*).

To accurately assess the impact of these factors, the *DSR* employs a weight distribution approach through a

game-theoretic Data Envelopment Analysis (*DEA*). This method optimizes each node's contribution to *DSR* by selecting ideal weights for each factor and incorporating adjustments based on the system's configuration. The calculation of *DSR* combines both multiplicative and additive methods, ensuring a comprehensive assessment. By considering all primary nodes and their respective factors, the *DSR* metric provides a detailed evaluation of the system's resilience against both physical and cyber challenges. Weights for each primary node factor influencing *DSR* are determined using a game-theoretic Data Envelopment Analysis (*DEA*) approach, allowing for the optimization of each node's contribution to *DSR*. This method incorporates a minimum threshold for factor weights, adaptable based on system configuration. It is defined as a combination of multiplicative and additive methods:

$$DSR = \sum_{j=1}^n \left(\prod_{i=1}^m (f_{ij})^{w_i^j} \right)$$

3.2.4 Case Studies

A case study with a modified IEEE-123 node test feeder will be used as our example network to realize the implications of the metrics provided in the previous section. In this case, the modified feeder has 85 nodes with spot loads. Our objective is to understand how the presence of IoT devices impacts the resilience of electrical distribution systems. To explore this, we have adapted these 85 nodes to incorporate IoTs. Specifically, we designed 50 of these nodes as cyber-power primary nodes associated with IoTs, 20 nodes as cyber-power primary nodes but without IoTs, and the remaining nodes are considered physical primary nodes. Furthermore, with the metrics formulated around IoTs, specific parameters for our analysis are set

accordingly. The reporting time interval (Δt) is set to 1, the total observed period (T) is 12, and the weights for the current and previous time periods (w_t and w_{t-}) are both set to 0.5. Initializing with normal operations, suppose the *ITS* for our power system remains perfect at 1.0 until a certain point of time, $t = 14$, as shown in Fig. 9. Imagine two scenarios: in the first, a solar panel gets accidentally disconnected due to maintenance work but is quickly fixed. We may define this event as an unintended substation event (sse). This incident temporarily lowers the trustability score of the involved IoT devices, showing how sensitive the system is to even unintentional disruptions. The values of *ITS* during that event drop to around 0.75 and return to 1 as soon as the event is cleared at $t = 16$, as shown in Fig. 9.

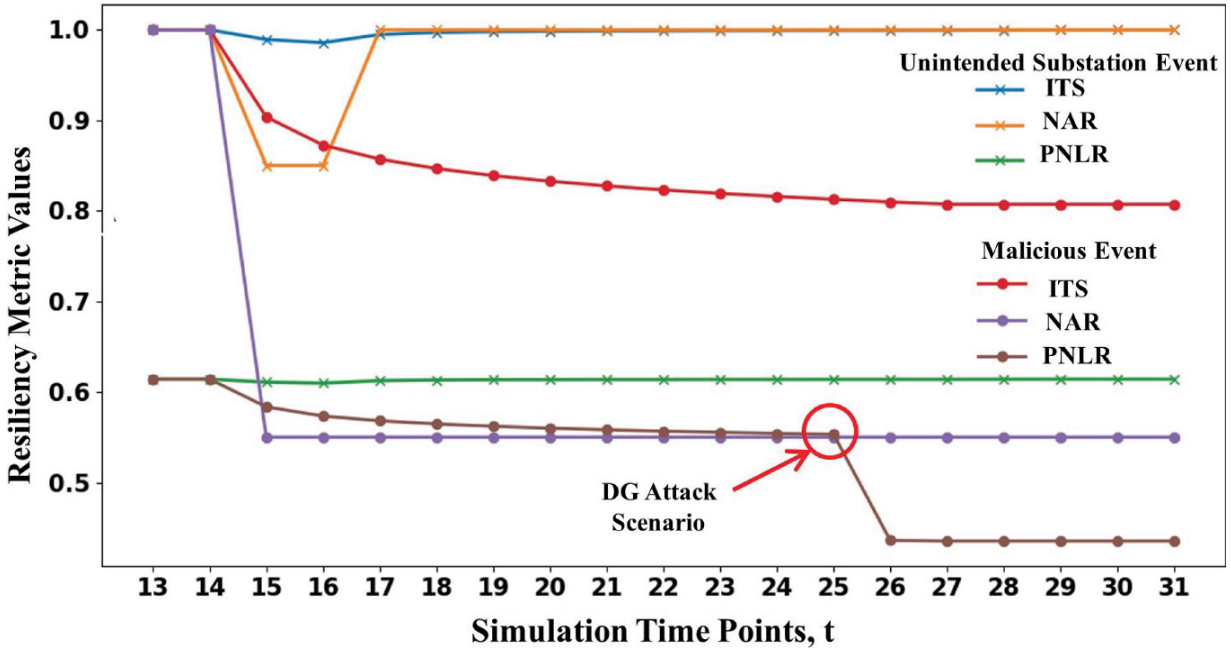


Fig. 9 NAR, ITS, and PNL for the unintended substation event (sse) and malicious event (me)

The second scenario highlights the risk of malicious activities and their potential to undermine the trust and reliability of the network. For this study, we assume a specific primary node in the distribution system connects to

seven houses or connections, each equipped with IoT-based devices. These devices include smart inverters for managing solar PV and battery systems. It is further assumed that three out of these seven connections use devices from the same manufacturer, which are known to have certain vulnerabilities. In the second scenario, attackers exploit vulnerabilities in the IoT-based inverters provided by the same manufacturer, affecting the solar PV and battery systems of two houses and one commercial building. This attack is initiated at $t = 14$, leading to the generation of irregular data points from the PVs and batteries due to malicious activities. The Non-Anomaly Ratio (*NAR*) for one of the affected houses, as illustrated by the line 'NAR_me' in Fig. 9, shows a significant drop, reflecting the impact of the attack. Since three out of the seven users connected to the primary node are targeted, the IoT Trustability Score (*ITS*) for that node deteriorates significantly, as shown by the 'ITS_me' line in Fig. 9. As the attackers maintain full access to the compromised inverters, the production of anomalous data points persists, and the *ITS* remains compromised, highlighting the vulnerability of the system to such malicious interventions and its impact on the network's reliability and trust.

On the other hand, the *PLNR* score, in the first scenario, as shown in Fig. 9, remains mostly stable during the time of disturbance and overall simulation. This stability is due to the constancy of all contributing factors except for the *ITS*, which experiences only minor fluctuations during the event. However, in the second scenario, a noticeable drop in *PLNR* is observed in Fig. 9. It starts at $t = 14$, concurrent with a drop in *ITS* followed by a malicious event. At $t = 25$, the situation escalates when the attacker manages to sever the connections to the solar photovoltaic systems and batteries at the compromised sites. This act directly impacts the node's ability to generate power, leading to a

notable drop in available power generation. As a result, PNL_R starts to fall, reflecting the node's reduced capacity to maintain stability and supply electricity reliably. This decline in resilience is captured by the 'PNLR_{me}' in Fig. 9, illustrating how the combined effect of reduced trustability and power generation compromises the node's overall resilience.

Assuming that the primary node's resilience spans across all secondary voltage areas-key operational zones of the distribution system-it significantly influences the system's overall resilience. Thus, we set minimum thresholds for factors affecting this resilience: 0.4 for Primary Node Resilience (*PLNR*), and 0.1 each for Available Power Outflow (*APO*), Primary Node Centrality (*PNC*), and Device and Communication Vulnerabilities in the Primary Network (*DCVP*). These factor values and weights are assessed at each time step, t , to determine the distribution system's resilience, following the detailed discussion in Sect. 3.2.3.

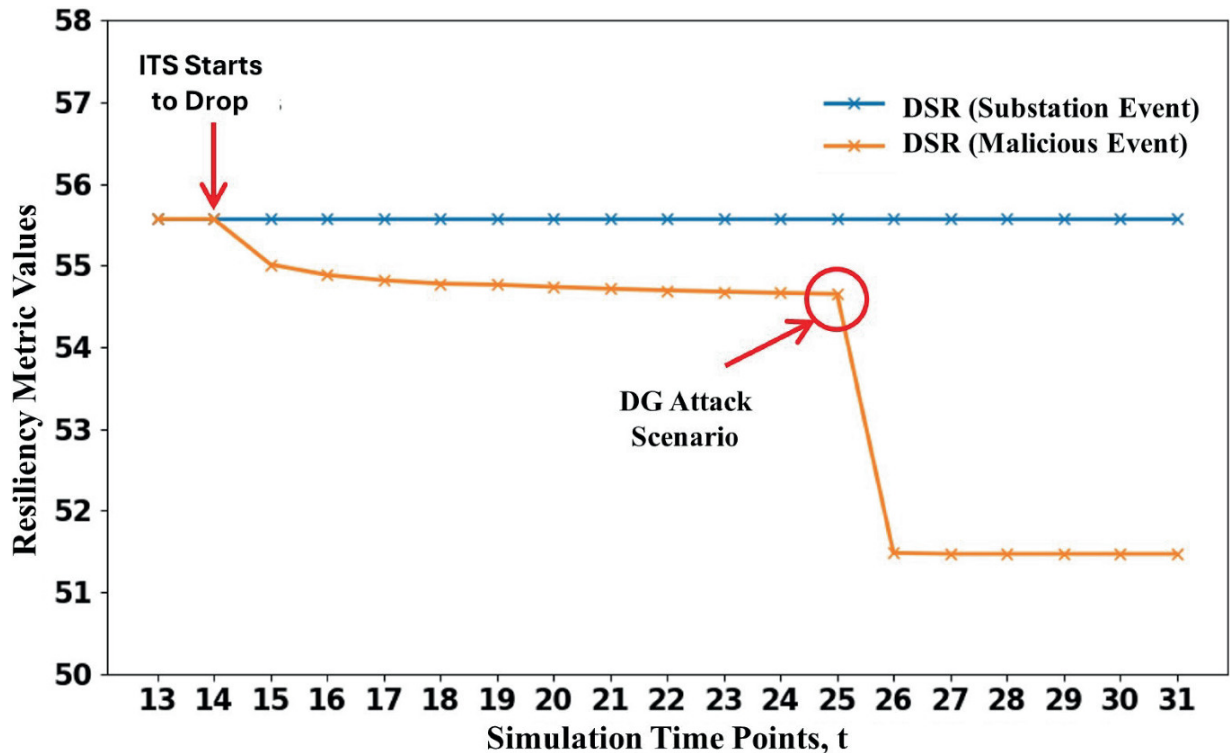


Fig. 10 DSR for the unintended substation event (sse) and malicious event (me)

The first scenario does not affect the secondary network significantly, hence the impact on the primary network should be even less. The assumption is supported by the “DSR_sse” results from Fig. 10.

However, the second scenario is expanded to present a widespread malicious attack targeting IoT-based inverters from a specific manufacturer within 30 cyber-physical primary nodes. Starting at $t = 14$, this orchestrated attack causes a significant decline in the *ITS* across all affected nodes, consequently dropping each node’s *PLNR*. This collective reduction in *PNLR* across 30 nodes leads to a noticeable decrease in *DSR*. By $t = 25$, as the attackers sever connections to solar PVs and batteries, the loss in generation capability deteriorates the drop in both *PNLR* for individual nodes and *DSR* overall. The scenario is compounded by the reduction in Available Power Outflow (APO) due to decreased generation, leading to a further decline in *DSR*, depicted by the “DSR_me” in Fig. 10.

4 Use Cases of Adaptive Resilience Metrics

4.1 Cyberattack-Resilient Volt-Watt Control in DER-Rich Distribution Grid

The ANSI C84.1-2020 rule suggests that the voltage in low-voltage (LV) power distribution networks should stay very close to the expected level, not swinging too much above or below the acceptable limits [54]. To keep the voltage steady, traditionally we use tools like adjustable transformers, voltage regulators, and capacitor banks. However, these devices introduce inherent complexity to the network, in which the complexity increases with the addition of more solar panels, wind turbines, or other

distributed energy resources (DERs). These green sources are a potential support for the modern grid system, but they can make it harder to keep the voltage steady, especially when not many people are using electricity. Increasing use of these DERs, therefore, could lead to voltage instability. According to IEEE-1548, renewable energy resources can help control this voltage by either supplying reactive power to the local loads during peak demand or reducing the power during low-demand periods. This helps keep the electricity flow stable, and owners of the DERs can also act as prosumers, a term to define both consumer and producer, to gain financial benefits through the redundant supply of power. Controlling such erratic voltage fluctuations can be done by methods such as VAR absorption or active-power curtailment, which is sometimes referred to as “Volt-Watt” control. While it is crucial to operate these resources at their maximum power point, relying solely on VAR control may prove insufficient to maintain voltages within acceptable limits. Consequently, there may be a need to curtail active power via volt-watt control to avert potential issues. The challenge is balancing the grid while maximizing the benefits from these DERs without compromising grid stability, especially in the distribution network, where, among other complexities, the resistance-to-reactance (R/X) ratio is critical. The complexity gives rise to vulnerabilities in the network with the risk of cyber attacks, which could deteriorate the operational process to maintain optimal voltage levels. To address challenges associated with ensuring grid stability, securing grid operation, and optimizing the use of renewable energy resources, methods, such as “Volt-Watt” to maintain voltage levels to acceptable limits can be crucial [55]. The Volt-Watt control function or algorithm is developed to help manage the feeder voltage and maintain optimal voltage levels required by the integrated power network. The algorithm puts a restriction on the active

power generated by the DERs according to the required voltage limits. The algorithm initiates the changes whenever the voltage surpasses a predefined threshold. The optimization of the volt-watt problem is formulated as follows,

$$\min_{\mathbf{x}} \sum_{\forall i} f_i(x_i) \quad (16a)$$

$$\text{s.t.} \quad \underline{y}_i \leq y_i(x_i) \leq \bar{y}_i \quad (16b)$$

$$\underline{x}_i \leq x_i \leq \bar{x}_i \quad (16c)$$

Here, the objective function ($f_i : \mathbb{R} \rightarrow \mathbb{R}$) must satisfy μ -strong convexity and l -smoothness criteria. The problem exhibits complete decomposability with respect to x_i , where these variables are interconnected only through the function y_i , which may inherently be non-linear. A linear relationship between x_i and y_i is identified for updating primal variables in the optimization problem solution. The plant is used to determine $y_i(x_i)$, which is then employed in updating the dual variables, making our approach feedback-based or dynamic. The iterative use of this feedback-based methodology serves to progressively mitigate model inaccuracies stemming from the approximated relationship.

We assume a linear power flow approximation for the distribution system. Consider an unbalanced radial distribution network with three phases and $N + 1$ nodes, where the node set is defined as $\mathcal{N} = \{0, 1, \dots, N\}$. This simplified model linearizes the power flow equations, omitting line losses and assuming balanced node voltages. The linear approximation of the power flow equations discussed is,

$$\tilde{\mathbf{v}} = \bar{\mathbf{Z}}^P \tilde{\mathbf{P}} + \bar{\mathbf{Z}}^Q \tilde{\mathbf{Q}} + v_0 \mathbf{1}_{3N} \quad (17)$$

where the network voltage vector is $\tilde{v} = [v_1 \dots v_N]^T$ with $v_j = [|V_j^a|^2, |V_j^b|^2, |V_j^c|^2]^T$, and $\forall j \in \mathcal{N}$, active power injection vector is $\tilde{P} = [p_1 \dots p_N]^T$ where $p_j = [p_j^a, p_j^b, p_j^c]^T, \forall j \in \mathcal{N}$, reactive power injection vector is $\tilde{Q} = [q_1 \dots q_N]^T$ where $q_j = [q_j^a, q_j^b, q_j^c]^T, \forall j \in \mathcal{N}$, substation end voltages are $v_0 \mathbf{1}_{3N}$ and resistances and reactances of the distribution network are $3 - \phi$ matrices $\bar{Z}^P$ and $\bar{Z}^Q$ [56].

The active power injection in (17) is separated into curtailable $\tilde{P}^C$ and fixed $\tilde{P}^F$ components, where, $\tilde{P} = \tilde{P}^F + \tilde{P}^C$. The network-wide voltage profile is given as,

$$\tilde{v}(\tilde{P}^F) = \bar{Z}^P \tilde{P}^C + \tilde{v}^{unc} \quad (18a)$$

$$\tilde{v}^{unc} = \bar{Z}^P \tilde{P}^F + \bar{Z}^Q \tilde{Q} + v_0 \mathbf{1}_{3N} \quad (18b)$$

where $\tilde{v}^{unc}$ is a factor dependent on $\tilde{P}^F$ and $\tilde{Q}$. Here, $\tilde{v}(\tilde{P}^F)$ characterizes the input-output relationship between active power curtailment and the network voltage profile. At time t , if the active power curtailment vector throughout the network is denoted as $\tilde{P}^F(t)$ and, following its implementation, the measured voltage is $v(t)$, the resultant Lagrangian multiplier dictates the control action $\tilde{P}^F(t+1)$.

The computation of controller set-points involves the use of the primal auxiliary variable $\hat{p}_i$, as well as the dual auxiliary variables ξ_i , $\bar{\lambda}_i$, and $\underline{\lambda}_i$ (with each of these variables being vectors for all three phases) at each node. It is assumed that voltage controllers exist for all phases at a given time t .¹ During this time, measurements are taken for the voltages at the DER nodes, denoted as $v_i^{meas}(t)$, as well as the active power capability based on the Maximum Power Point (MPP), denoted as $p_i^{mpp}(t)$. With the available values of $\hat{p}_i(t)$, $\xi_i(t)$, $\bar{\lambda}_i(t)$, $\underline{\lambda}_i(t)$, and exchanged information from neighboring DERs, the auxiliary variables are

updated. Subsequently, active power injection set-points, denoted as $p_i^{inj}(t+1)$, are computed and applied locally.

Each controller with DER in a corresponding node j ($j \in \mathcal{N}$) goes through four different steps that are essential to obtain the set-points updated with the Volt-Watt control.

Step 1: (Measurement) Measure All local phase voltages $v_j(t)$ are measured at all available phases.

Step 2: (Calculate) Calculate, $\hat{p}_j(t+1)$, $\xi_j(t+1)$, $\bar{\lambda}_j(t+1)$, $\underline{\lambda}_j(t+1)$, using the following equations:

$$\hat{p}_j(t+1) = \hat{p}_j(t) - \alpha \left\{ (\bar{\lambda}_j(t) - \underline{\lambda}_j(t)) + \sum_{\forall i \in \mathcal{N}_j} [\bar{Z}^P]_{ji}^{-1} \left[f'_i(\hat{p}_i(t)) + \text{ST}_{-cp_j^{mpp}(t)}^0 (\xi_i(t) + c\hat{p}_i(t)) \right] \right\} \quad (19a)$$

$$\xi_j(t+1) = \xi_j(t) + \beta \frac{\text{ST}_{-cp_i^{mpp}(t)}^0 (\xi_j(t) + c\hat{p}_j(t)) - \xi_j(t)}{c} \quad (19b)$$

$$\bar{\lambda}_j(t+1) = \bar{\lambda}_j(t) + \gamma \left[(v_j^{meas}(t) - \bar{v}_j) \right]^+ \quad (19c)$$

$$\underline{\lambda}_j(t+1) = \underline{\lambda}_j(t) + \gamma \left[(\underline{v}_j - v_j^{meas}(t)) \right]^+ \quad (19d)$$

where $\mathcal{N}_j$ represents the set of all neighboring nodes of node j for every $j \in \mathcal{N}$.

Step 3: (Active Power Set-Point Deployment): The active power injection set-point at time $t+1$ is determined as,

$$p_j^{inj}(t+1) = \left[p_j^{mpp}(t+1) + [\hat{p}_j(t+1)]_{-p_j^{mpp}(t)}^0 \right]_{p_j^{mpp}(t)}^{p_j^{mpp}(t+1)} \quad (20)$$

Step 4: (Communication): Neighboring DER nodes receive values

$$f'_j(\hat{p}_j(t+1)) + \text{ST}_{-cp_j^{mpp}(t+1)}^0 (\xi_j(t+1) + c\hat{p}_j(t+1)).$$

The essence of the Volt-Watt control mechanism lies in its ability to curtail active power output from DERs based on predefined voltage thresholds, thus preventing over-voltage incidents. The control strategy, formalized in Eqs. (19, 20), utilizes a distributed feedback approach that enables localized decision-making and rapid adaptation to changing network conditions. By leveraging the linearized power flow model, the algorithm ensures the optimal balance between power injection and voltage stability, fostering a resilient distribution network. DERs, equipped with converter-inverter technology, play a crucial role in the Volt-Watt control scheme. The innovative topology of these systems allows for seamless integration and real-time communication with the grid's control center, facilitating the exchange of crucial operational data. This coordination is critical to ensuring the effective implementation of Volt-Watt control actions, particularly during orchestrated or unplanned grid disturbances.

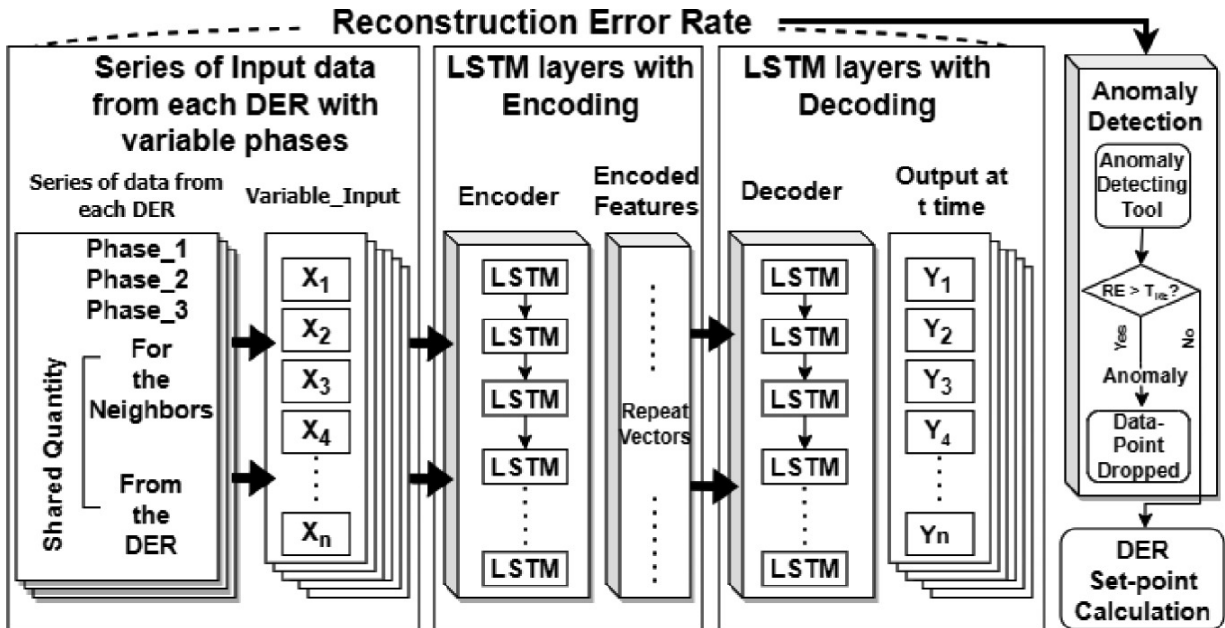


Fig. 11 Multivariate LSTM for anomaly detection and mitigation

The vulnerability of distributed control systems to cyberattacks poses significant risks to grid stability. The

proposed Volt-Watt control strategy incorporates a multivariate LSTM-autoencoder-based anomaly detection mechanism that scrutinizes data for inconsistencies indicative of cyber threats. By identifying and isolating anomalous data (Fig. 11), the control system prevents malicious commands from influencing DER operations, thus maintaining voltage levels within safe margins even under adverse conditions. The effectiveness of the Volt-Watt control strategy, along with the robustness of the anomaly detection and mitigation framework, was validated using a modified IEEE 123-bus distribution network. Simulated cyberattack scenarios, including MitM, DoS, and replay attacks, demonstrated the system's resilience, as evidenced by the stability of voltage profiles (Fig. 12) and the successful rejection of compromised data points (Fig. 13). These results underscore the critical role of advanced control strategies and cybersecurity measures in ensuring the reliable operation of DER-rich distribution networks [57].

In conclusion, the integration of Volt-Watt control with advanced DER technologies and cybersecurity mechanisms presents a comprehensive approach to mitigating the impacts of cyber-attacks on the power distribution network. This strategy not only ensures voltage stability but also paves the way for the secure and efficient integration of renewable energy sources into the grid.

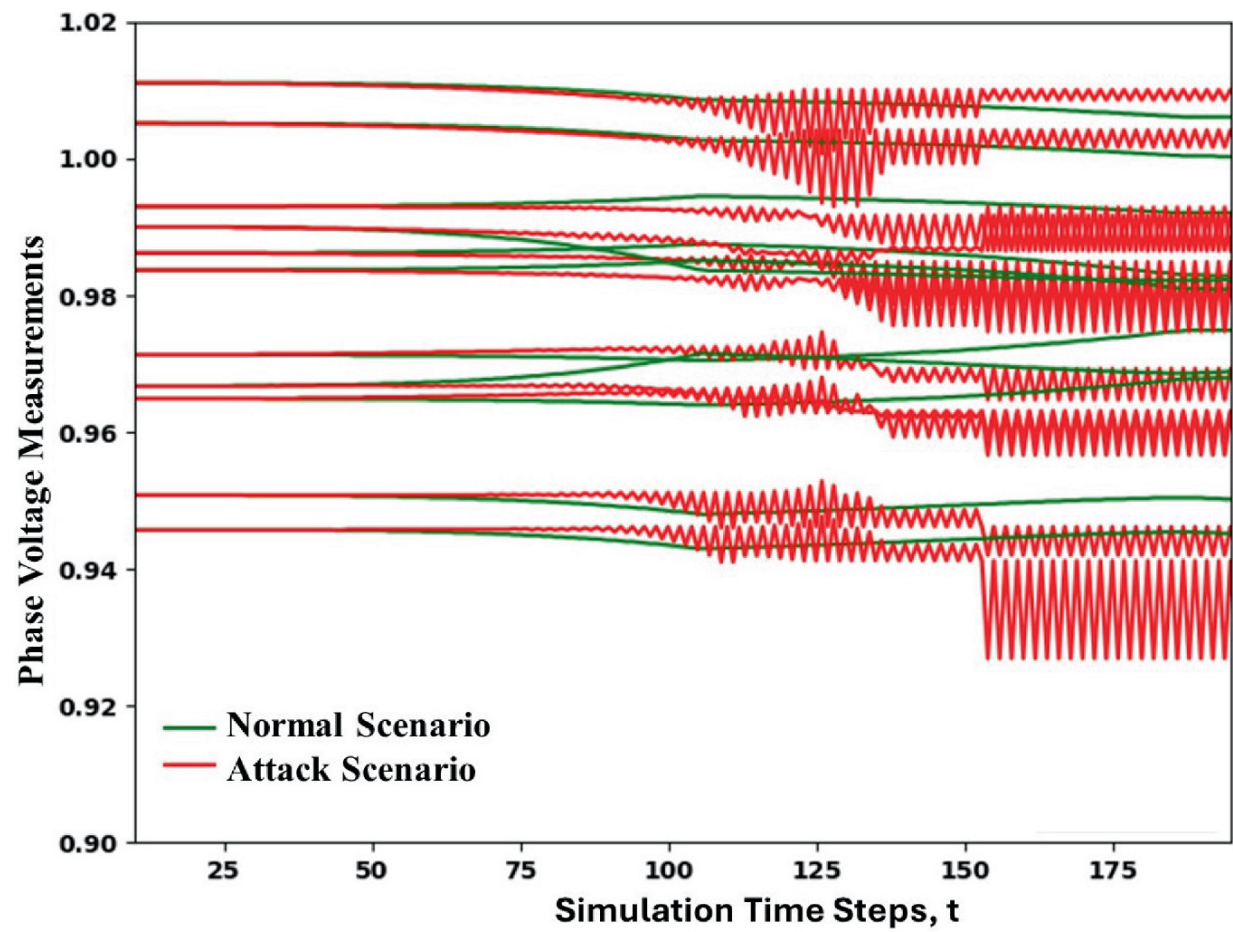


Fig. 12 Phase voltages at DERs node during normal control operation and under attack scenarios

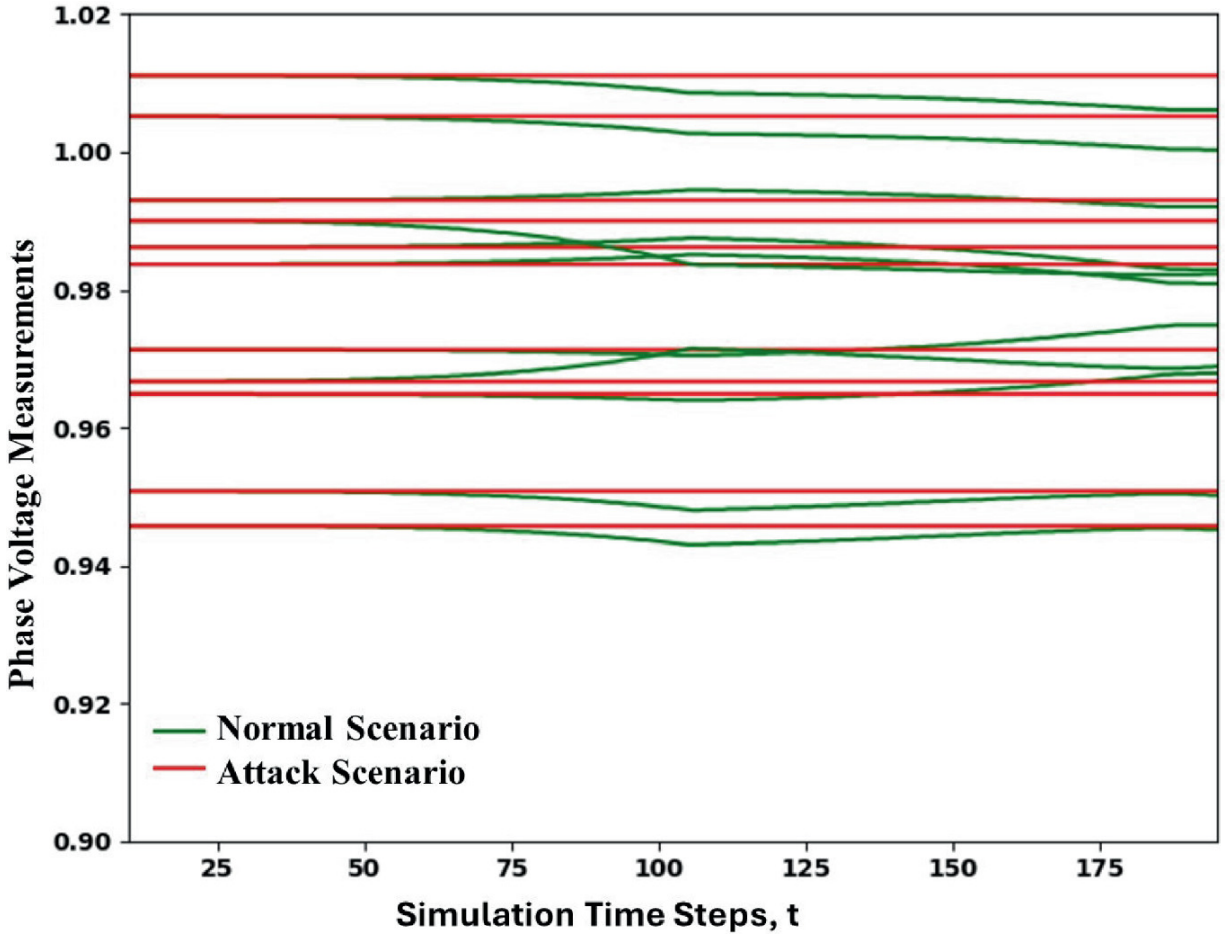


Fig. 13 Phase voltages at DERs nodes during normal control operation and anomalous data dropped scenarios

4.2 Resilience-Driven Distribution System Restoration with IoT

The evolving cyber-physical distribution system [58–60] includes intelligent Internet of Things (IoT) devices, making it more adaptable. IoT is a fast-growing technology that can facilitate connectivity between distributed energy resources and vital facilities [60, 61], thus facilitating resilient restoration utilizing different resilience metrics [19]. This improves system resilience by enabling alternative power flow paths, reducing single points of failure, ensuring maximum DER utilization and critical load fed, and improving response capabilities during extreme events.

4.2.1 Resilience-Driven Restoration with IoT

The restoration method incorporates energy-based generation and load balance to ensure continuous connectivity of selected loads until the restoration of normal operating conditions. It also considers the demand response mechanism in load assignment by utilizing IoT-based resources.

In the restoration method, several modules work together to maximize the value of factors that are important for resilience metrics. It utilizes the forecasted load profiles with different levels of criticality and source profiles to ensure continuous power supply during the whole restoration operation period. Overall, it is comprised of the initialization of available resources, energy-based optimization for primary-level resource determination, loss and topology determination, and secondary-level load shedding considering demand response-based load profiles. The overall formulation utilizes a hierarchical structure.

The primary-level optimization is formed as linear programming, which balances load and generation at the primary voltage level, considering criticality and various demand response participations of house loads. Generally, distribution system loss depends on several system configuration factors, such as lines, transformers, capacitors, insulators, etc. With the proliferation of DERs in distribution systems (consisting of single, three, and split phases), loss analysis with traditional theoretical approaches becomes increasingly complex. This challenge has been addressed by developing a deep neural network (DNN) loss model tuned with extensive hyper-parameter optimization for distribution system components. An equivalent graph network is developed using a one-to-one mapping of the primary-level of the distribution system, where the nodes represent all primary-level nodes of the distribution system, and the edges represent all the

distribution lines and switches. A minimum loss path algorithm uses this graph network and determines the minimum loss path where the system loss of the distribution system, consisting of single, three, and split phases, is estimated using DNN models of system components to match critical loads with generation while ensuring the radiality of the network. This provides the new switching status of the reconfigured system.

The optimization of the secondary node level is a binary linear programming problem that involves two binary variables for each house participating in the demand response, one for the main load and the other for the other load on the house. Houses without demand response have only one binary variable for the secondary level. The number of binary variables depends on the number of houses in the secondary level of the primary node. The load assigned by the primary level optimization is considered as available generation sources for the secondary loads. The goal of the secondary level optimization is to connect house loads based on their criticality level as long as the available generation sources can supply energy to each discrete load. Thus, this identifies the houses that need to be disconnected from the grid to maintain power supply to the remaining connected loads.

4.2.2 Use Case

A three-phase, unbalanced distribution system with edge IoT devices is modeled which incorporates detailed secondary feeder nodes besides primary feeder nodes to capture the closer-to-real-world dynamics. Furthermore, secondary feeder expansions such as weather-dependent HVAC, PV, and water heater components are added with the scheduling ability to turn devices on/off as needed to incorporate realistic system-like granularity. Resilience studies require data from various sources to capture the real-world dynamics within a distribution system. The

distribution system model has been expanded to include residential and commercial buildings, edge devices (IoT), occupant-based load dynamics, and distributed energy resources (DERs) like photovoltaic panels, battery energy storage systems, and diesel generators, as shown in Fig. 14 in GridLAB-D. This detailed model mimics real world representation of distribution system and used to validate our proposed restoration method [62].

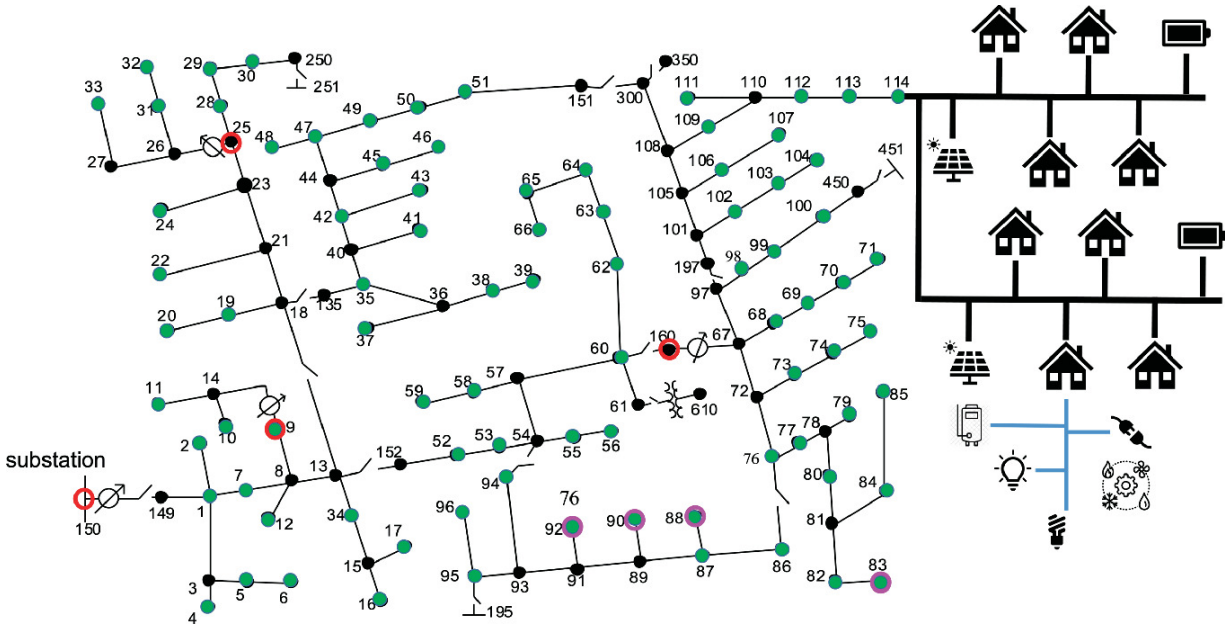


Fig. 14 Secondary feeder detail for the GridLAB-D IEEE-123 node test system

5 Summary and Path Forward

5.1 Summary

To meet renewable energy goals worldwide, distributed energy resources are quickly being integrated into distribution grids. DERs offer various benefits, including peak load reduction, decentralization, lower energy costs, resilience to disasters, and flexibility in energy management. However, integrating DERs presents challenges such as grid stability and voltage regulation. Apart from that, increasing weather and cyber events

further impact grid resilience. Resilience in distribution systems is crucial for ensuring reliable electricity delivery, particularly during extreme events or disruptions, safeguarding communities, and critical infrastructure. Resilience evaluation encompasses qualitative and quantitative approaches, including resilience curves and metrics tailored for distribution systems based on topological, curve-based, probabilistic, reliability-based, and cost-based techniques. Topology-based metrics evaluate power system performance based on its topology, utilizing optimization techniques and graph theory. Curve-based metrics: These assess system resilience using characteristic curves, dividing performance into categories like pre-interruption, disruption, recovery speed, and status. Probabilistic metrics analyze the stochastic nature of disruptive events. Reliability-based metrics focus on the system's ability to maintain reliable operation under various conditions, using indices like availability and risk-based measures. Cost-based metrics: These evaluate resilience by considering the economic costs associated with grid events. However, the dynamic and uncertain nature of electric distribution systems highlights the need for an adaptive resilience metric. Adaptive resilience metrics are essential to continuously monitor, analyze, and adjust resilience strategies in response to evolving threats and changing system circumstances.

5.2 Path Forward

For a future path forward for distribution system resilience, several key considerations need to address current limitations and enhance practicality.

1. Firstly, to make resilience metrics practical, we need to simplify them. This means taking complicated metrics and turning them into simpler ones that still tell us important things about how resilient our systems are,

but still feasible to implement. This helps make sure the metrics are easier to use and match what we can actually do with the resources we have.

2. Secondly, addressing data needs is crucial for robust resilience assessment. Establishing comprehensive data repositories and validation frameworks is essential to ensuring the accuracy and reliability of resilience metrics.
3. Thirdly, baselining resilience metrics poses challenges, particularly in defining thresholds for acceptable performance for the current system at hand. Thus, while assessing current resilience levels is valuable, the focus should shift towards comparing resilience before and after interventions. This approach provides insights into the effectiveness of resilience-enhancing measures and informs future decision-making processes.
4. Fourthly, integrating resilience-driven practices into planning and operations is important. This involves embedding resilience considerations into decision-making processes, such as infrastructure investments, system upgrades, and proactive and emergency responses.
5. Lastly, increasing collaboration between vendors and utilities is essential for advancing resilience-driven practices in planning and operations.

Acknowledgements

Authors would like to acknowledge partial support from the NSF CPS, US DOE RACER, US DOE Solar Testbed and US DOE GRIP awards to support this work. We are also thankful to technical contributions of past researchers in

our research group including Dr. Shikhar Pandey and Dr. Gowtham Kandaperumal.

References

1. International Renewable Energy Agency (IRENA) (2024) Renewable energy roadmaps. <https://www.irena.org/Energy-Transition/Outlook/Renewable-energy-roadmaps>. Accessed 28 March 2024
2. Wu D, Kalathil D, Begovic MM, Ding KQ, Xie L (2022) Deep reinforcement learning-based robust protection in der-rich distribution grids. *IEEE Open Access J Power Energy* 9:537–548
[Crossref]
3. Foroutan A, Basumallik S, Srivastava A (2023) Estimating and calibrating der model parameters using Levenberg-Marquardt algorithm in renewable rich power grid. *Energies* 16(8):3512
[Crossref]
4. Nair VJ, Venkataramanan V, Haider R, Annaswamy AM (2022) A hierarchical local electricity market for a der-rich grid edge. *IEEE Trans Smart Grid* 14(2):1353–1366
[Crossref]
5. Vosughi A, Tamimi A, King AB, Majumder S, Srivastava AK (2022) Cyber-physical vulnerability and resiliency analysis for der integration: a review, challenges and research needs. *Renew Sustain Energy Rev* 168:112794
[Crossref]
6. Chen C, Wang J, Ton D (2017) Modernizing distribution system restoration to achieve grid resiliency against extreme weather events: an integrated solution. *Proc IEEE* 105(7):1267–1288
[Crossref]
7. Shaoyun G, Jifeng L, Hong L, Yuchen C, Zan Y, Jun Y (2019) Assessing and boosting the resilience of a distribution system under extreme weather. In: *IEEE power and energy society general meeting (PESGM)*. IEEE, pp 1–5
8. Liu W, Li L, Hu J, He X, Zhang Y, Wu J (2023) A long-term reliability assessment method for active distribution networks considering the impacts of extreme weather events. In: *Proceedings of the 2023 3rd international conference on energy engineering and power systems (EEPS)*. IEEE, pp 1025–1030
9. IEEE (1971) IEEE standard definitions in power operations terminology including terms for reporting and analyzing outages of electrical transmission and distribution facilities and interruptions to customer

service. Institute of Electrical and Electronics Engineers (IEEE), Piscataway, NJ

10. Halverson JB, Rabenhorst T (2013) Hurricane sandy: the science and impacts of a superstorm. *Weatherwise* 66(2):14-23
[\[Crossref\]](#)
11. Tervo R, Láng I, Jung A, Mäkelä A (2020) Predicting power outages caused by extratropical storms. *Nat Hazards Earth Syst Sci Disc* 2020:1-26
12. Zimba SK, Houane MJ, Chikova AM (2020) Impact of tropical cyclone IDAI on the southern African electric power grid. In: *IEEE PES/IAS PowerAfrica*. IEEE, pp 1-5
13. Gautam A, Sudhakar G, Gupta M, Shukla R, Porwal R, De D, Narasimhan S (2021) Proactive operation strategy to enhance resiliency of Indian power system during super cyclone Amphan. In: *Proceedings of the 2021 9th IEEE international conference on power systems (ICPS)*. IEEE, pp 1-6
14. Soonee S, Narasimhan S, Nallarasan N, Rathour HK, Yadav G, Bhan S, Mali R (2015) Impact of very severe cyclone hudhud on power system operation. In: *Annual IEEE India conference (INDICON)*. IEEE, pp 1-5
15. Rong M, Han C, Liu L (2010) Critical infrastructure failure interdependencies in the 2008 Chinese winter storms. In: *Proceedings of the 2010 international conference on management and service science*. IEEE, pp 1-4
16. Kemabonta T (2021) Grid resilience analysis and planning of electric power systems: the case of the 2021 Texas electricity crises caused by winter storm. *Electr J* 34(10):107044
[\[Crossref\]](#)
17. Mitchell JW (2013) Power line failures and catastrophic wildfires under extreme weather conditions. *Eng Fail Anal* 35:726-735
[\[Crossref\]](#)
18. Stillman R, Darveniza M (1991) Risk evaluation-power system induced bush and grass fires and the catastrophe potential. *IEEE Trans Reliab* 40(3):309-315
[\[Crossref\]](#)
19. Sarker PS, Sadanandan SK, Srivastava AK (2022) Resiliency metrics for monitoring and analysis of cyber-power distribution system with IoTs. *IEEE Internet Things J*
20. Sarker PS, Rafy MF, Srivastava AK, Singh R (2023) Cyber anomaly-aware distributed voltage control with active power curtailment and ders. *IEEE Trans Ind Appl*

21. Majumder S, Vosughi A, Mustafa HM, Warner TE, Srivasava AK (2023) On the cyber-physical needs of der-based voltage control/optimization algorithms in active distribution network. IEEE Access
22. Venkataramanan V, Hahn A, Srivastava AK (2024) Measuring and enabling resiliency for microgrid systems against cyber-attacks. Resil Power Distrib Syst 12:101-123
[Crossref]
23. Global assessment report on disaster risk reduction. United Nations Office for disaster risk reduction (UNDRR). <https://www.undrr.org/media/48008/download>. Accessed 28 March 2024
24. The University of Texas at Austin (2024) Ercot blackout 2021. <https://energy.utexas.edu/ercot-blackout-2021>. Accessed 2 March 2024
25. Major power outage events. <https://poweroutage.us/about/majorevents>. Accessed 2 March 2024
26. Entous A, Nakashima E, Eilperin J (2016) Russian hackers penetrated U.S. electricity grid through a utility in Vermont. https://www.washingtonpost.com/world/national-security/russian-hackers-penetrated-us-electricity-grid-through-a-utility-in-vermont/2016/12/30/8fc90cc4-ceec-11e6-b8a2-8c2a61b0436f_story.html
27. IR Alert H-16-056-01. <https://www.cisa.gov/news-events/ics-alerts/ir-alert-h-16-056-01>. Accessed 20 March 2024
28. U.S. Department of Homeland Security (2018) DHS resilience framework. https://www.dhs.gov/sites/default/files/publications/dhs_resilience_framework_july_2018_508.pdf. Accessed 20 March 2024
29. U.S. Department of Energy (2019) North American energy resilience model. <https://www.energy.gov/oe/articles/north-american-energy-resilience-model-july-2019>. Accessed 20 March 2024
30. Kramer A, Belding S, Coney K (2023) Title of the report. <https://www.nrel.gov/docs/fy23osti/84493.pdf>. Accessed 28 March 2024
31. Stankovic A (2018) The definition and quantification of resilience. In: IEEE PES industry technical support task force. Piscataway, NJ, pp 1-4
32. Beasley B, Greenwald J (2018) Power system resilience: a primer. Bipartisan Policy Center, Washington, DC
33. Chiu B, Bose A (2020) Resilience framework methods and metrics for the electricity sector. In: IEEE power and energy society, resource center

34. Watson J-P, Guttromson R, Silva-Monroy C, Jeffers R, Jones K, Ellison J, Rath C, Gearhart J, Jones D, Corbet T et al (2014) Conceptual framework for developing resilience metrics for the electricity oil and gas sectors in the united states. In: Sandia national laboratories, albuquerque, nm (United States), technical report
35. Afzal S, Mokhlis H, Illias HA, Mansor NN, Shareef H (2020) State-of-the-art review on power system resilience and assessment techniques. IET Gener Transm Distrib 14(25):6107–6121
[\[Crossref\]](#)
36. Gholami A, Shekari T, Amirion MH, Aminifar F, Amini MH, Sargolzaei A (2018) Toward a consensus on the definition and taxonomy of power system resilience. IEEE Access 6:32035–32053
[\[Crossref\]](#)
37. Yodo N, Wang P (2016) Engineering resilience quantification and system design implications: a literature survey. J Mech Des 138(11):111408
[\[Crossref\]](#)
38. Dehghani A, Sedighizadeh M, Haghjoo F (2021) An overview of the assessment metrics of the concept of resilience in electrical grids. Int Trans Electr Energy Syst 31(12):e13159
[\[Crossref\]](#)
39. Kwasinski A (2016) Quantitative model and metrics of electrical grids' resilience evaluated at a power distribution level. Energies 9(2):93
[\[Crossref\]](#)
40. Chanda S, Srivastava AK (2016) Defining and enabling resiliency of electric distribution systems with multiple microgrids. IEEE Trans Smart Grid 7(6):2859–2868
[\[Crossref\]](#)
41. Bajpai P, Chanda S, Srivastava AK (2016) A novel metric to quantify and enable resilient distribution system using graph theory and Choquet integral. IEEE Trans Smart Grid 9(4):2918–2929
[\[Crossref\]](#)
42. Pandey S, Chanda S, Srivastava AK, Hovsopian RO (2020) Resiliency-driven proactive distribution system reconfiguration with synchrophasor data. IEEE Trans Power Syst 35(4):2748–2758
[\[Crossref\]](#)
43. Panteli M, Mancarella P, Trakas DN, Kyriakides E, Hatziargyriou ND (2017) Metrics and quantification of operational and infrastructure resilience in power systems. IEEE Trans Power Syst 32(6):4732–4742
[\[Crossref\]](#)

44. Liang Z, Kavousifard A, Su W (2018) Resilient restoration for distribution system operators when facing extreme events. In: North American power symposium (NAPS). IEEE, pp 1–6
45. Luo D, Xia Y, Zeng Y, Li C, Zhou B, Yu H, Wu Q (2018) Evaluation method of distribution network resilience focusing on critical loads. IEEE Access 6:61633–61639
[\[Crossref\]](#)
46. Wei Y, Ji C, Galvan F, Couvillon S, Orellana G (2013) Dynamic modeling and resilience for power distribution. In: Proceedings of the 2013 IEEE international conference on smart grid communications (SmartGridComm). IEEE, pp 85–90
47. Umunnakwe A, Huang H, Oikonomou K, Davis K (2021) Quantitative analysis of power systems resilience: standardization, categorizations, and challenges. Renew Sustain Energy Rev 149:111252
[\[Crossref\]](#)
48. Kwasinski A (2014) Field technical surveys: an essential tool for improving critical infrastructure and lifeline systems resiliency to disasters. In: IEEE global humanitarian technology conference (GHTC). IEEE, pp 78–85
49. Poudel S, Dubey A, Bose A (2019) Risk-based probabilistic quantification of power distribution system operational resilience. IEEE Syst J 14(3):3506–3517
[\[Crossref\]](#)
50. Manshadi SD, Khodayar ME (2015) Resilient operation of multiple energy carrier microgrids. IEEE Trans Smart Grid 6(5):2283–2292
[\[Crossref\]](#)
51. Yao S, Wang P, Zhao T (2018) Transportable energy storage for more resilient distribution systems with multiple microgrids. IEEE Trans Smart Grid 10(3):3331–3341
[\[Crossref\]](#)
52. Chanda S, Srivastava AK, Liu CC (2024) Concepts of resiliency. Resil Power Distrib Syst 12:1–33
53. Kandaperumal G, Pandey S, Srivastava A (2021) Awr: anticipate, withstand, and recover resilience metric for operational and planning decision support in electric distribution system. IEEE Trans Smart Grid 13(1):179–190
[\[Crossref\]](#)
54. American National Standards Institute (2020) American national standard voltage ratings for electric power systems and equipment (60 Hz)

55. Sarker PS, Majumder S, Rafy MF, Srivastava AK (2022) Impact analysis of cyber-events on distributed voltage control with active power curtailment. In: Proceedings of the 2022 IEEE international conference on power electronics, drives and energy systems (PEDES), pp 1–6
 56. Kekatos V, Zhang L, Giannakis GB, Baldick R (2016) Voltage regulation algorithms for multiphase power distribution grids. *IEEE Trans Power Syst* 31(5):3913–3923
[\[Crossref\]](#)
 57. Ilić MD, Xie L, Khan UA, Moura JM (2010) Modeling of future cyber-physical energy systems for distributed sensing and control. *IEEE Trans Syst Man Cybern A Syst Hum* 40(4):825–838
[\[Crossref\]](#)
 58. Sridhar S, Hahn A, Govindarasu M (2011) Cyber-physical system security for the electric power grid. *Proc IEEE* 100(1):210–224
[\[Crossref\]](#)
 59. Farhangi H (2009) The path of the smart grid. *IEEE Power Energ Mag* 8(1):18–28
[\[Crossref\]](#)
 60. Chiang M, Zhang T (2016) Fog and IoT: an overview of research opportunities. *IEEE Internet Things J* 3(6):854–864
[\[Crossref\]](#)
 61. Morello R, De Capua C, Fulco G, Mukhopadhyay SC (2017) A smart power meter to monitor energy flow in smart grids: the role of advanced sensing and IoT in the electric grid of the future. *IEEE Sens J* 17(23):7828–7837
[\[Crossref\]](#)
 62. Sarker PS (2023) Enabling cybersecure and resilient smart distribution grid with edge devices. PhD Dissertation, West Virginia University
-

Footnotes

¹ If DERs are not present in all the phases, this will be indicated through appropriate constraints.

Maintaining Energy System Resilience Through Adaptation

Larry Hughes¹ 

(1) Department of Electrical and Computer Engineering,
Dalhousie University, Halifax, NS, B3H 4R2, Canada

 **Larry Hughes**

Email: Larry.Hughes@dal.ca

Abstract

A resilient energy system is one that ensures its end users receive the energy they require at an affordable price. The available energy must also be considered acceptable, meeting certain standards. A resilient energy system is one that is energy secure. However, if an event occurs that disrupts the end user's supply of energy or makes it unaffordable or unacceptable, and the system is unable to recover, it must adapt to its new state. In this chapter, we review the basics of energy systems and how events can change them; we then consider the different ways in which a system can adapt to its new normal.

Keywords Energy security – Adaptation – Energy demand – Energy supply

1 Introduction

In 2015, the United Nations released its 2030 Agenda for Sustainable Development. Only one of the Agenda 17's goals refers to energy directly, Goal 7: Affordable and Clean Energy. Most of the remaining goals are affected by the energy we all use globally, either directly (for example, driving a vehicle) or indirectly (for example, receiving goods sent from another jurisdiction). The energy, used worldwide in energy consuming sectors (such as transportation, buildings, and industry) and services (including lighting, heating, and cooling), comes from secondary energy sources (such as electricity and diesel), obtained from a variety of primary energy sources (such as coal, crude oil, natural gas, uranium, and various renewables).

The conversion of primary energy to secondary energy takes place in an energy system. The system consists of three types of processes: those that convert energy from primary energy sources into secondary energy; those that store energy for subsequent use; and those that transfer energy from conversion or storage processes to end-user energy sectors and services. The energy system also interacts with entities external to it, including sources of primary energy, the environment, end users, and those responsible for the system.

Energy systems are not static. Processes within the system can be affected by external or internal events that impact the system's flows of energy. When an event occurs, the stress on the system and its primary or secondary energy suppliers and end-users can increase. These external entities expect the system to respond to the event and return to a low-stress or stress-free state. If this can occur within a tolerable length of time, the system is said to be resilient.

However, there can be situations when the event makes it impossible for the system to return to its original state, meaning the stress level remains high. If this occurs for an intolerable period, the system must evolve to a new state that is then resilient to the event. This is adaptation.

For an energy system and its entities to be resilient, those responsible for the system must be able to adapt the system to changing events.

In the next section, we consider the fundamental structures in an energy system, the processes and various flows between the processes, and how the system can be represented. We build on this simple model in the third section by applying the International Energy Agency's definition of energy security to the processes and flows that constitute an energy system. The definition is extended to recognize the impact of political and societal views on energy systems and their security.

In the fourth section, we examine events, stress, and how processes can change their state from Normal to Tension, and finally, Disruption. This is followed in the fifth section showing how events, their occurrence, and duration affect processes and their state. How processes remain resilient in the threat of events is discussed in section six, while section seven explains the three fundamental adaptation policies (Reduce, Replace, and Restructure) and what they can mean to a process and its flows.

In the seventh section, policy implications of adaptation are discussed. A summary of the work follows, concluding the chapter and briefly reviewing the material covered.

2 Energy Systems

A system can be defined as “a group of interacting, interrelated, or interdependent elements forming, or regarded as forming, a collective entity” [1]. The “collective

entity”, that is, the system, can be discussed in terms of two models [98]:

- The *environmental model*, defining the relationships between the system and the external entities with which it interacts.
- The *behavioural model*, defining the processes internal to the system that allow it to interact with the external entities.

To understand an *energy* system, it is necessary to distinguish between what is inside the system, determining its behaviour, and what is outside the system in its environment. For example, the critical minerals required for renewable energy technologies such as storage batteries and wind turbines can be considered part of the system or external to it. If the technologies are considered external to the system, but in its environment, our only concern is with the technology that uses the critical minerals (i.e., the wind turbines and the storage). However, if we consider the critical minerals as being part of (that is, internal to) the system, not only are we concerned with the technology that uses the critical minerals, but the minerals, their extraction, processing, and environmental and social impacts.

The boundary between the external entities interacting with the system (its environment) and its internal processes (determining its behaviour) is specified by the system modeller and those using the system.

2.1 Representing an Energy System

An anthropogenic energy system takes primary energy sources (such as crude oil, coal, natural gas, or wind) and converts them into secondary energy sources (such as gasoline, aviation fuel, or electricity). The secondary energy can then be supplied to meet the needs of an energy sector or, depending on the level of granularity of the

model, an end-user's energy service (such as a vehicle, a hot water tank, a light bulb, or an appliance). A generic energy system is shown in Fig. 1.

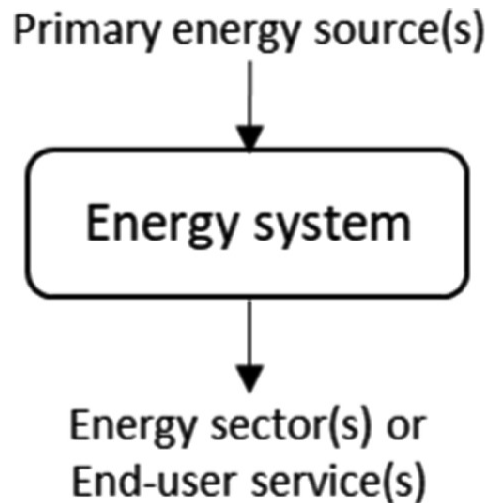


Fig. 1 An energy system

An energy system consists of internal processes. Each process has four input flows and three output flows. The input flows cause the process to change state and potentially the state of the other processes or external entities (such as a primary energy provider or an energy sector or end-user energy service) it interacts with. The basic representation of a process, which can be considered an energy system in its own right, is shown in Fig. 2.

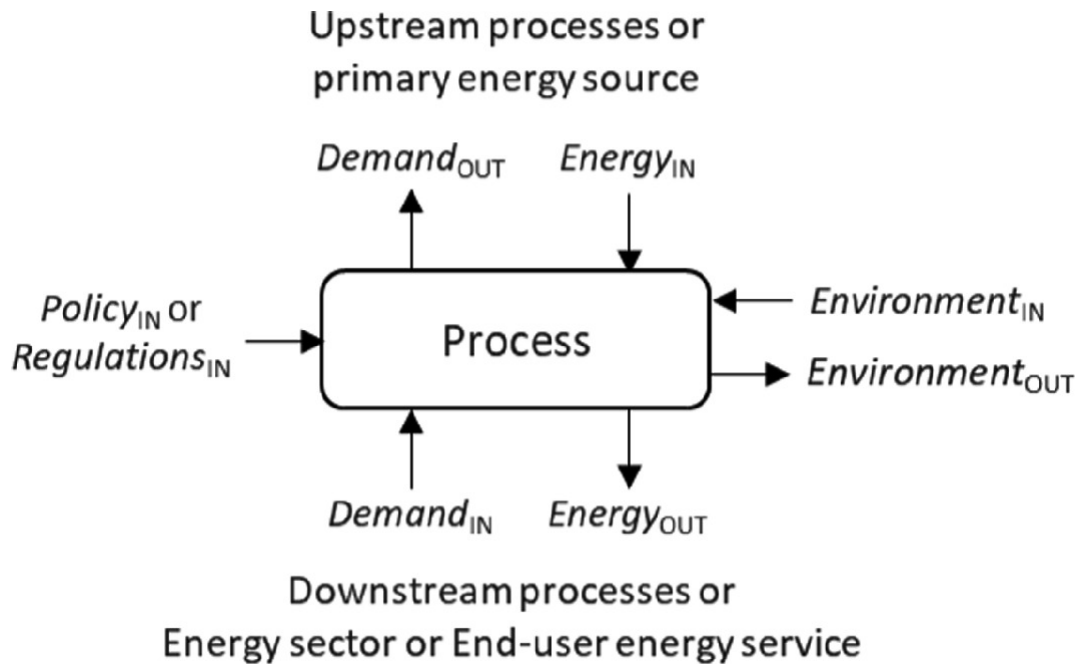


Fig. 2 Basic structure of a process and its flows

A process responds to the demand for energy ($Demand_{IN}$) from a downstream process or an external entity. The process should meet this demand with an equivalent volume of energy ($Energy_{OUT}$). To supply $Energy_{OUT}$, the process requests the required volume of energy ($Demand_{OUT}$) from an upstream process or an external entity. The required volume of energy ($Energy_{IN}$) is subsequently supplied to the process.

The process has other interactions in addition to the energy-demand flows. Each process interacts with the environment in some way, potentially taking from the environment ($Environment_{IN}$) or emitting to the environment ($Environment_{OUT}$), or both. Processes are typically subject to regulations, from governments, corporations, or both, dictating its operation ($Policy_{IN}$ or $Regulations_{IN}$).

2.1.1 Flows

A flow carries a description of whatever is being transferred. For example, the Demand and Energy flows can specify the volume and type of energy required or supplied, respectively. Policy flows can refer to documents that dictate a process's permissible and prohibited activities. The Environment flows indicate what is being taken from or supplied to the environment; this can vary and depends on the aspect of the environment under consideration. Flows are represented as labeled arrows.

2.1.2 Processes

There are three types of process:

Conversion: A conversion process takes an input energy flow ($Energy_{IN}$), typically a primary energy source, and converts it to a secondary energy source ($Energy_{OUT}$). Examples of conversion processes and their primary and secondary energy are listed in Table 1.

Table 1 Conversion process examples

Primary energy source	Process	Conversion	Secondary energy
Wind	Wind turbine	Wind → turbine → electricity	Electricity
Sunlight	Solar panel	Photons → photovoltaic effect → electricity	Electricity
Crude oil	Refinery	Crude oil → refined products	Gasoline, diesel, aviation fuel, light oil
Uranium	Nuclear reactor	Heat → steam → turbine → electricity	Electricity, heat
Water	Hydroelectric station	Water → turbine → electricity	Electricity
Wood	Wood stove	Biomass → combustion → heat	Heat

Conversion is not restricted to primary energy sources. A secondary source can be converted into another secondary source, usually of the same type. For example, an electrical substation can take a high voltage source of electricity and step it down (convert it) to a lower voltage for distribution to end-user customers, while inverters convert direct current to alternating current. A natural gas liquefaction facility converts natural gas into liquefied natural gas (LNG), which is subsequently gasified back to natural gas [99].

The operation of any electrical generating station has a primary $Energy_{IN}$ (such as coal for a thermal generating plant, crude oil for a refinery, or sunlight for a solar panel) that is converted into a secondary $Energy_{OUT}$ (e.g., electricity from a thermal generating station or a solar panel, albeit one being alternating current and the other direct current). A refinery converts primary sources of crude oil or bitumen ($Energy_{IN}$) into secondary refined oil products such as gasoline or aviation fuel ($Energy_{OUT}$). In some cases, a conversion process might require several energy inputs. For example, refineries often require a source of hydrogen produced from natural gas to create its products.

Most conversion processes interact with their environment. Thermal power stations, including nuclear reactors, often require a source of cooling water to help condense steam [50]. The heat removed, in the form of a higher temperature water, is returned the environment.

Wind turbines and solar panels, because their operation is determined by their environment and are considered non-dispatchable, do not have a $Demand_{IN}$ or $Demand_{OUT}$. (We might wish for sun or wind, but wishful thinking does not translate into $Demand_{OUT}$!) The representation of a process and its flows are shown in Fig. 3a.

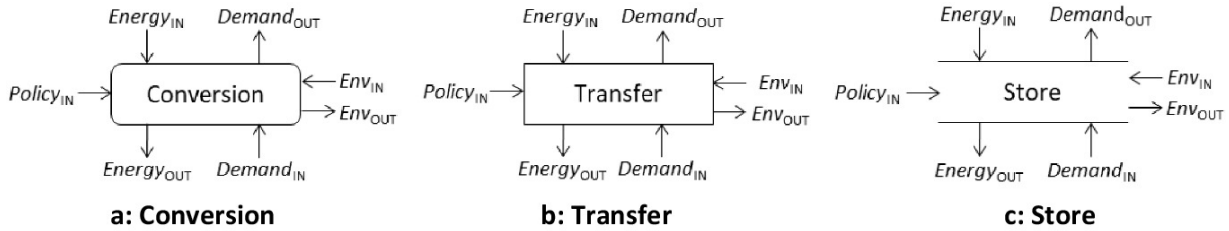


Fig. 3 Shapes representing processes (Env refers to the environment flow)

A jurisdiction's energy system need not have a conversion process to meet all its secondary energy requirements. For example, many jurisdictions do not have refineries because of the cost and environmental considerations. Instead, a regional refinery might supply those jurisdictions without a refinery with secondary energy products such as gasoline and aviation fuel.

Although not necessarily considered part of an energy system, an end-user's services can be thought of as a conversion process, converting secondary energy to meet the needs of a service: a LED light converts electricity into lumens; an automobile converts a liquid fuel or electricity into movement; and a heat pump can take electricity and energy (from the air, ground, or water) and uses ("converts") this energy it into heat for space heating.

Transfer: The energy produced by a conversion process is not always in the same location as the sector or end-user services for which it is intended. One such example of this is the electricity produced by a hydroelectric station situated in a mountainous region with end-users in locations hundreds of kilometres away. In this case, the secondary energy (electricity) must be transferred or transported from where it is produced to where it is needed by the end-user. The flows associated with a transfer process are shown in Fig. 3b.

Other examples of processes designed for transferring energy from one location to another include crude oil carriers, LNG carriers, oil pipelines, natural gas pipelines,

electrical distribution grids, and dung collection by women in rural India [18].

In most instances, it takes energy to move the energy. A liquefied natural gas carrier, moving LNG from a port where it is liquefied to a destination port where it is gasified requires energy to move the vessel; one approach is to use the natural gas that boils off as the fuel [23]. Liquid fuels shipped in pipelines need pumps to push the fuel to the offtake facility, requiring the pipeline to have two energy inputs: the fuel being moved and the energy for the pumps, often taken directly from the fuel in the pipeline [100].

Store: In some instances, the energy produced by a conversion process is not required for immediate use. Rather than wasting the energy, energy producers will store the energy for subsequent use or sale. Two of the more common forms of secondary energy storage are tank farms for oil products and batteries to store electricity. Primary energy can also be stored: natural gas is often pumped into salt caverns during the summer for use during the winter months [90]; heat accumulators for morning peak use in district heating systems [26]; a reservoir for hydroelectric station holds water as potential energy; a snowpack located in a mountainous region with streams flowing into a hydroelectric dam's reservoir [7]; and a woodshed for a household using biomass for heating or cooking are all examples of stores [9].

An energy service, such as an automobile, also requires some form of storage, either for the liquid fuel for an internal-combustion vehicle or batteries to store electricity in an electric vehicle. A hybrid-electric vehicle has two energy stores: a tank for the fuel required for its generator-engine and a battery for electricity supplied by the vehicle's generator or braking system [87].

The maximum capacity of the store is determined by its operators and specified as a $Policy_{IN}$. The process operating the store would determine when more $Energy_{IN}$ is needed by signalling $Demand_{OUT}$. Energy is removed ($Energy_{OUT}$) when there is a request for energy ($Demand_{IN}$); see Fig. 3c.

As with the transfer process, the $Energy_{IN}$ and $Energy_{OUT}$ flows of a store are the same type of energy. However, the volume of energy put into the store need not equal the volume removed; this is determined by the efficiency of the store. For example, the volume of electricity removed from a battery depends on the efficiency of the charging equipment and any losses suffered by the battery due to factors such as temperature, depth of discharge, and age [60]. In a tank farm storing petroleum products, losses can occur from the evaporation of volatile organic compounds (VOCs) being released to the environment [31].

2.2 Example

Processes can be linked together to form a chain, showing how external entities can interact with the processes in an energy system.

For example, we consider the volume of natural gas required to supply 20 kWh to an electric vehicle charger.

We start at the bottom left of the system shown in Fig. 4 with the end-user service, the EV charger, that requires 20 kilowatts for one hour. The $Demand_{OUT}$ from the charger is 20 kWh. Losses in grid, primarily as heat, mean the natural gas plant must supply the grid with 21.7 kWh to compensate for the 92% efficiency (η) of the grid. The turbines in the natural gas plant are 40% efficient, meaning that it requires the equivalent of 54.3 kWh or 0.196 GJ of natural gas [64].

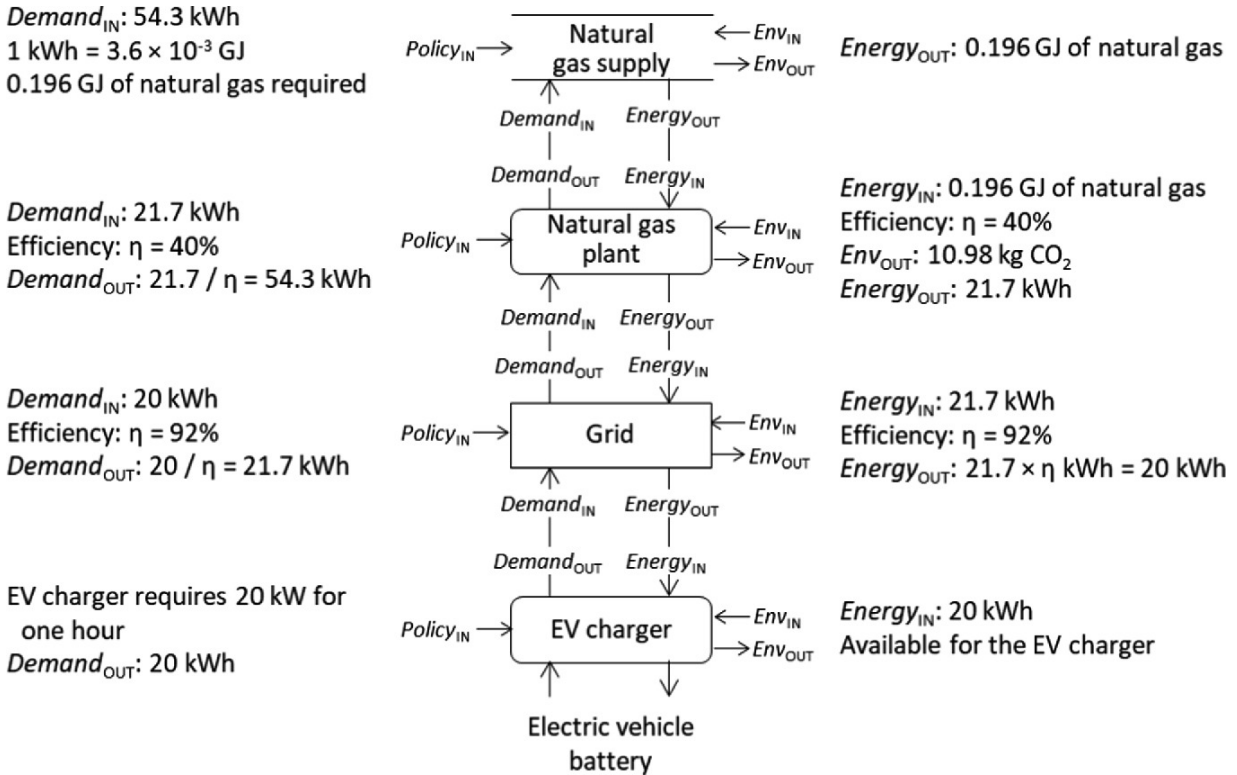


Fig. 4 End-user service (EV charging) demand for electricity and the effect of efficiency on energy demand

From top right of the figure, the natural gas supplier sends 0.196 GJ of natural gas to the natural gas plant. The plant operates at 40% efficiency, producing 21.7 kWh of electricity and emitting 10.98 kg of CO₂. The energy is supplied to the grid. The EV charger receives 20 kWh from the grid because of the grid's inefficiencies.

3 Summary

An energy system is responsible for supplying secondary energy to its end-use sectors and services. This is achieved using three types of process: conversion (converting primary to secondary energy), transfer (moving primary or secondary energy between processes or to a sector or service), and storage (holding primary or secondary energy until it is needed).

Each process is associated with a number of flows. These do not actually transfer anything; they simply indicate what passes between processes inside the system or between processes and those entities outside the system.

We will refer to an energy system's processes and their flows throughout the remainder of this chapter.

4 Energy Security

Energy security is essential for any energy system. The International Energy Agency's definition of energy security has evolved over time, from "The uninterrupted physical availability [of energy] at a price which is affordable, while respecting environment concerns" [36], to "Ensuring the uninterrupted availability of energy sources at an affordable price" [38]. Although "respecting environmental concerns" has been removed and the two fundamental requirements, *availability* and *affordability*, remain; a third requirement, the *acceptability* of the energy system in terms of energy justice influences how we approach energy security [52].

We see the broad perspective of this view of energy security in the United Nation's Sustainable Development Goal 7 (SDG 7), notably, "ensuring access to affordable, reliable, sustainable and modern energy for all" [83]. This objective is what any end-user of an energy system expects:

- The energy must be *affordable*. If the energy supply is unaffordable, the end-user may as well not have a supply of energy.
- The energy must be *accessible* and *reliable*. If the energy supply is not available when needed, the end-user may have difficulty performing tasks required for their occupation, education, and family or community.
- The energy must be *sustainable* and *modern*. A modern energy system is one which is acceptable to the

community it serves (from IEA [37]):

- A minimum level of electricity is available for households.
- Fuels for cooking and heating have minimum harmful effects on health and environment.
- Enables productive economic activity.
- Electricity for public services such as health facilities, schools, and street lighting.

SDG 7's objective is essentially a variation on the IEA's definition of energy security.

4.1 Energy Security Indicators

In this chapter, we use the and the IEA's definition of energy security to define three energy security indicators: availability, affordability, and acceptability of an energy supply. The indicators will show the state of the process or entity's resilience and whether it needs to be adapted. Changes in the indicators can signal the improvement or deterioration of energy security [33].¹

4.1.1 Availability

A process expects a supply of energy (represented by the $Energy_{IN}$ flow) from an upstream process or primary energy supplier in response to the process's demand (represented by its $Demand_{OUT}$ flow). Similarly, a sector or a service expects a supply of energy matching its demand from an upstream process.

For the process, sector, or service to operate successfully, the $Energy_{IN}$ flow must equal or exceed the $Demand_{OUT}$ flow. This is the availability indicator metric, AVA:

$$AVA = \frac{Energy_{IN}}{Demand_{OUT}} \geq 1$$

If the $Energy_{IN}$ to $Demand_{OUT}$ ratio equals or exceeds 1, the supply of energy meets the demand. However, if the ratio is less than 1, $Demand_{OUT}$ exceeds supply, meaning that the process, sector, or service is unable to operate successfully.

If a process has multiple $Energy_{IN}$ flows, their individual contributions can be used to determine the availability of the energy supply [35].

4.1.2 Affordability

A unit of energy has a price. The price represents the various prices associated with the different processes in the energy chain (conversion, transport, and storage) and, if applicable, the price of the primary energy.² These prices must be accounted for by the end user and upstream processes such as the provider of the energy to the end user. The cost of the energy consumed is the result of the price of the energy and the volume of energy consumed. Other costs can be included in the overall price of the energy, including value added taxes [77], and if the energy affects the environment flows, carbon taxes [95].

In its simplest interpretation, the total cost is the affordability of an energy flow. Examining long-term datasets of energy costs shows whether the price of the energy flow is increasing or decreasing. While it is possible to use the energy's long-term cost trends as an indication of the energy affordability, the IEA's definition of energy security requires that an energy flow will be available at a "price which is affordable". For this, it is necessary to combine the cost of the energy flow with other indicator values to obtain the flow's affordability.

For example, the energy consumer requires an energy budget to pay for the expected cost of energy consumed. The ratio of the energy budget to the cost of the energy can be used as the affordability indicator metric, AFF:

$$AFF = \frac{Budget\ for\ Demand_{OUT}}{Cost\ of\ Energy_{IN}} \geq 1$$

If the ratio produces a result that equals or exceeds 1, the energy supply is affordable and the consumer's energy supply is secure in terms of affordability. However, if the metric is less than one, the cost of energy exceeds the budget, meaning the energy is unaffordable and the consumer's energy supply is not secure.

The impact of an energy flow cost to a customer varies, often depending upon the customer's income—the lower the income, the larger the percentage required to cover the cost of the energy [25]. This interpretation of affordability refers to the ability-to-pay for a unit of energy.

The interpretation of affordability can also depend upon what the energy consumer represents. If it (and the data used) pertains to a regional, national, or supranational entity, the affordability indicator can be interpreted as the cost-per-unit of energy. On the other hand, if statistics allows the consumer to be defined at the household-level, the ability-to-pay can be used as the affordability indicator.

Regardless of how the affordability indicator is interpreted, if higher per-unit energy costs are regarded as being less secure than those with lower per-unit costs, a rise in the cost of energy will cause security to deteriorate, while a decline in the cost will cause security to improve.

4.1.3 Acceptability

The availability and affordability indicators require $Energy_{IN}$ flows to be associated with a volume and a price. The flow can be associated with other information as well. Acceptability can refer to any energy-related environmental impact including non-reusable resources (such as the lime used for capturing SO_2 in coal-fired power stations) [65], reusable resources (such as water for cooling thermal generating stations) [75], and others that may only be

partially reusable (such as metals retrieved from batteries) [66]. Other examples include the particulates released by the energy and the air, soil, and water emissions (i.e., environmental, the IEA's original definition) [3]; the country of origin of the primary energy source [84, 85]; and the impact on Indigenous groups that affect their lives or spiritual wellbeing [86]. These, and other issues, can be part of the acceptability indicator.

Unlike availability and affordability, the value of the acceptability indicator metric can be obtained in application-specific ways. As a generic approach, we set two limits: the lower, if met, means the flow is acceptable; the upper, if exceeded, means the flow is unacceptable. If the flow falls between the lower and upper limits, it is indeterminant and application-specific:

Acceptable: $f(Flow) < LowerLimit$

Indeterminant: $LowerLimit \leq f(Flow) < UpperLimit$

Unacceptable: $UpperLimit \leq f(Flow)$

The fact that acceptability can be qualitative rather than quantitative opens the debate surrounding an energy flow or a process that is responsible for the flow, and need not be straightforward, as with the removal of dams in the United State [51].

4.2 Indicator Interactions

The indicators do not exist in isolation. A simple example is a decline in the availability of an energy flow, leading to an increase in the energy price, affecting the consumer's ability to purchase the required energy. Similarly, an ability to pay for an energy supply does not necessarily mean that a flow is available, such as during a time of energy rationing. The different combinations are shown in Table 2.

Table 2 Interactions of availability and affordability metrics

Affordability	Availability	
	<1	≥1
<1	There is insufficient energy to meet demand and the process is unable to purchase what there is	There is sufficient energy, but the process is unable to purchase it
≥1	The process has sufficient funds, but there is insufficient energy to meet its demand	The process is in a secure state with sufficient funds to pay for the required energy

In some situations, acceptability can overrule both availability and affordability, changing the path of energy strategies or creating new ones. For example, as Indigenous peoples are doing in Canada [76].

5 Events

When asked what was the greatest challenge facing his time as prime minister, Harold Macmillan is said to have responded, “Events, dear boy, events” [63].

When an process’s $Demand_{OUT}$ is being met by an affordable and acceptable $Energy_{IN}$ flow, it is said to be in its *Normal* state. The process has a minimum of stress in the Normal state. However, if an event occurs that changes one or more of these indicators, the stress on the process will increase and it will enter a new state, either Tension or Disruption [35].

A process in the Tension state can continue operating, although not to the standard of the Normal state. Some processes can continue operating while experiencing increasing levels of stress; subsequent events may increase the stress but the process remains in the Tension state, changing from a Low-Tension state to a High-Tension state. If the stress increases beyond its tipping-point, the process ceases to operate and enters the Disruption state. The state

diagram in Fig. 5 shows the possible transitions a process undergoes each time an event occurs.

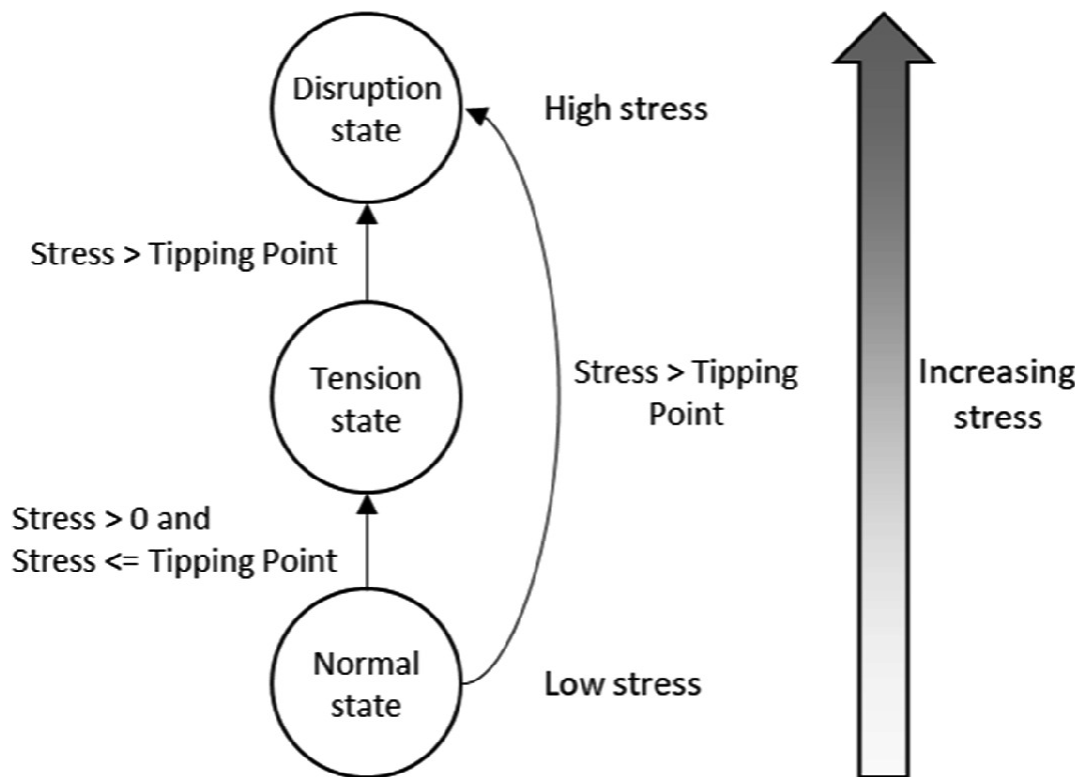


Fig. 5 State diagram showing state transitions with increasing stress levels [34]

5.1 Sources of Events

An event can be either internal or external.

5.1.1 Internal Events

An internal event affects one or more of its output flows. There are two types of internal events:

Accidental. Non-deliberate or erroneous actions taken by those responsible for the process. Examples of accidental events include misreading a meter, the installation of the wrong software, and the failure to communicate procedural changes.

Structural. Failures of equipment, environmental controls, or software due to aging, or other circumstances that exceed the process's expected operating parameters. Examples include the failure of a crude oil pipeline due to corrosion, the failure of a blowout prevention valve, and the failure of sensors to detect a change in stack emissions.

5.1.2 External Events

An external event occurs outside the process and affects one of its input flows:

Energy_{IN}. A change to the *Energy_{IN}* flow is detected as a change to either the supply of energy or its price. If the energy supply falls below the process's demand, the process will experience an availability event, whereas the cost of energy exceeding the process's energy budget results in an affordability event.

Demand_{IN}. A *Demand_{IN}* flow can indicate an increase or decrease in demand for *Energy_{OUT}*. If the demand for energy permanently exceeds the process's production of energy, the process experiences an underproduction energy event; without additional production, the process could lose market share.

Policy_{IN}. A *Policy_{IN}* event occurs when a policy is introduced which affects the process, one or more of its output flows, or both. Some policy events do not affect the process directly, instead an output flow is changed, affecting an upstream or downstream process.

Environment_{IN}. An *Environment_{IN}* event is one that originates from an external entity in the process's environment (other than a neighbouring process or the creator of policy). There are four types of *Environment_{IN}*

events that can affect the operation of the process, shown in Table 3.

Table 3 Types of $Environment_{IN}$ event

Event	Description	Examples
Unintentional	A non-malicious anthropogenic source that mistakenly affects the operation of the process	A backhoe operator digs a trench, damaging a natural gas pipeline
Resource	The loss of a resource on which the process depends	The loss of electricity that powers an oil pipeline's pumping station Lake water temperature increases reducing efficiency
Natural disaster	Natural disasters from both terrestrial and extra-terrestrial sources which threaten the process	A tsunami floods a nuclear reactor's backup generators A solar coronal mass ejection causes a geomagnetic storm, disrupting electrical services
Adversarial	Individuals, groups, organizations, or states that actively seek to disrupt the functioning of the process	A government agency inserts malicious software into a country's oil pipeline pumping stations, causing them to fail catastrophically

5.2 Events and Energy Security

Events affect processes. This can affect the flows between processes and entities. In the previous section, we introduced three indicators, availability, affordability, and acceptability, that allow us to examine the energy security of an energy system.

We now use the three indicators to show how events can affect the stress on an energy system's energy security.

5.2.1 Availability Events

An availability event is one which changes the availability of a process's $Energy_{IN}$ flow relative to its $Demand_{OUT}$ flow.

The possible effects of an availability event are illustrated in Fig. 6.

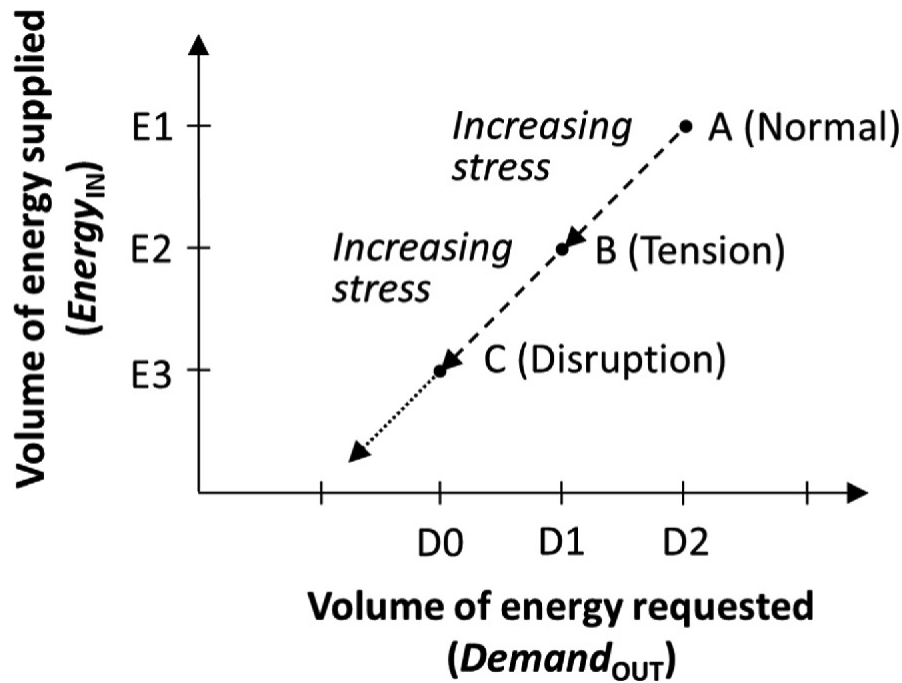


Fig. 6 Effect of availability events on stress

- A process is in its Normal state, 'A', if its $Demand_{OUT}$, $D2$, is equal to the energy supplied, $Energy_{IN}$, $E1$. In this case, the process's Availability requirement is being met, meaning it is in its Normal state with a stress of zero.
- If the supply of $Energy_{IN}$ declines (approaching $E2$ on the $Energy_{IN}$ axis), the available energy is less than $Demand_{OUT}$, $D2$. The process's stress increases.
- If the process can continue operating in a degraded fashion with less energy, its demand will begin to decline to $D1$ (the assumed minimum amount of energy the process requires to operate successfully); however, since $D2$ is no longer met, the process is now in the Tension state, 'B'.
- In the Tension state, $Energy_{IN}$ ($E2$) meets the process's minimum demand of $D1$. If the volume of $Energy_{IN}$ falls

below E2, the stress increases, passing the tipping point, putting the process into the Disruption state.

- The process remains in the Disruption state if $Energy_{IN}$ continues to decline.

If the process is in the Tension state, 'B', $Energy_{IN}$ must increase from E2 to E1 to return to the Normal state. Similarly, if the process is in the Disruption state, 'C', $Energy_{IN}$ must reach E2 (the tipping point, 'B'), if it is to return to the Tension state, and to reach E1 to return to the Normal state.

Examples of how the loss of availability increase the stress on an end-user's sectors and services include Russia's relentless attacks on Ukraine's energy infrastructure (notably district heating systems and electricity supply) and how Ukraine's energy engineers attempt to reduce the stress on the system [81]. The vulnerability of energy infrastructure to aerial attack and its importance as a strategic target from experience in the two Gulf wars is documented in [45, 68].

The Houthi attacks in the Strait of Bab al-Mandab and the prolonged drought in Panama are affecting the movement of oil through the Suez Canal and Panama Canal, respectively, and are increasing the stress on global energy supply [57].

The increasing demand for electric vehicles has made the availability of critical minerals, such as lithium, cobalt, and nickel for energy storage essential [72].

5.2.2 Affordability Events

A process is associated with an energy budget that is intended to meet the cost of the energy. When the volume of energy purchased at a certain price does not exceed the process's energy budget, the process is in its Normal state for affordability:

$$\text{Budget for } Energy_{IN} \geq (\text{Demand}_{OUT} \times \text{Price per unit } Energy_{IN})$$

An affordability event occurs when upstream events result in increases in the cost of (a downstream) process's $Energy_{IN}$ to the point where the energy budget is less than the total cost of the required volume of energy.

Figure 7 shows the various transitions that a process can undergo as the affordability of its $Energy_{IN}$ changes (this assumes that the volume and type of $Energy_{IN}$ remain unchanged, that is, it is available):

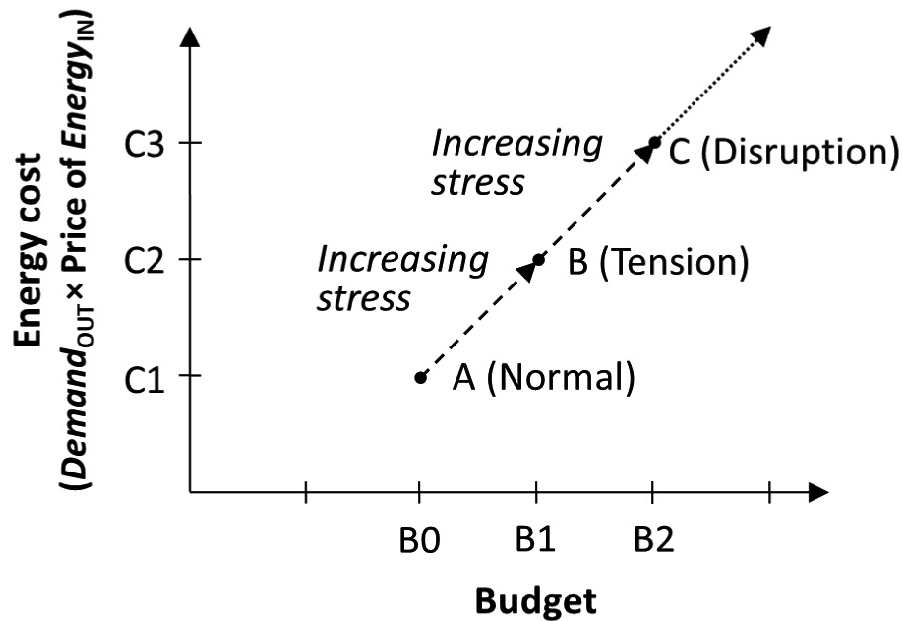


Fig. 7 Effects of affordability events on stress

- The process is in its Normal (affordability) state at point 'A' when its budget, B_0 , for the energy ($Energy_{IN}$) to be consumed is equal to the product of the unit energy price of the energy, C_1 .
- If the energy cost increases from C_1 and the budget can be increased, the stress on the process increases as the process must increase its budget to maintain the required demand.
- The process's maximum budget is B_1 , reached at point 'B'. Here, the energy budget is able to meet the required

demand at cost C2.

- At point 'B', the process is in its Tension state. If the energy cost increases beyond C2, the process must decrease its demand for energy so that the energy budget is not exceeded. This is the affordability tipping point.
- If the price continues to increase, the process will eventually reach a point where it is disrupted and unable to function at all. In the figure, this occurs at point 'C', with an energy cost of C3. This occurs at point 'C'. The process is now in the Disruption state. Any further price increases have little bearing on the process as it is unable function.

The budget is initially in one of two states:

At maximum ($A = B$): If the budget is at its maximum, points 'A' and 'B' are equal. Any increase in the energy price immediately puts the process into the Tension state. Further price increases will put it into the Disruption state.

Less than maximum ($A < B$): If the energy budget is less than the maximum possible budget at point 'A', a rise in price will result in increasing stress as the energy budget is raised at the expense of other budgets. Eventually a maximum will be reached (point 'B'); any further increases in the price will eventually put the process in the Disruption state.

Rising energy prices are often the result of increasing stress on the availability of an energy source or simply the thought of increasing stress. The threat of Russia's invasion of Ukraine in late 2021 and the eventual invasion caused rapid increases in European energy prices and affected the value of energy firms [17, 56].

Rising energy prices need not be the cause of an affordability event; constant energy prices during an economic crisis can make energy unaffordable for low-income households, putting them into a state of energy

poverty [27]. Energy poverty can also be an outcome of societal impact such as a lack of educational opportunities [70].

5.2.3 Acceptability Events

Acceptability events, unlike availability and affordability events that focus on supply and price respectively, can refer to a wide range of subjects and can be associated with any number of event-specific indicators. An acceptability indicator can be associated with any flow; acceptability can be described using a generic graph such as the one shown in Fig. 8.

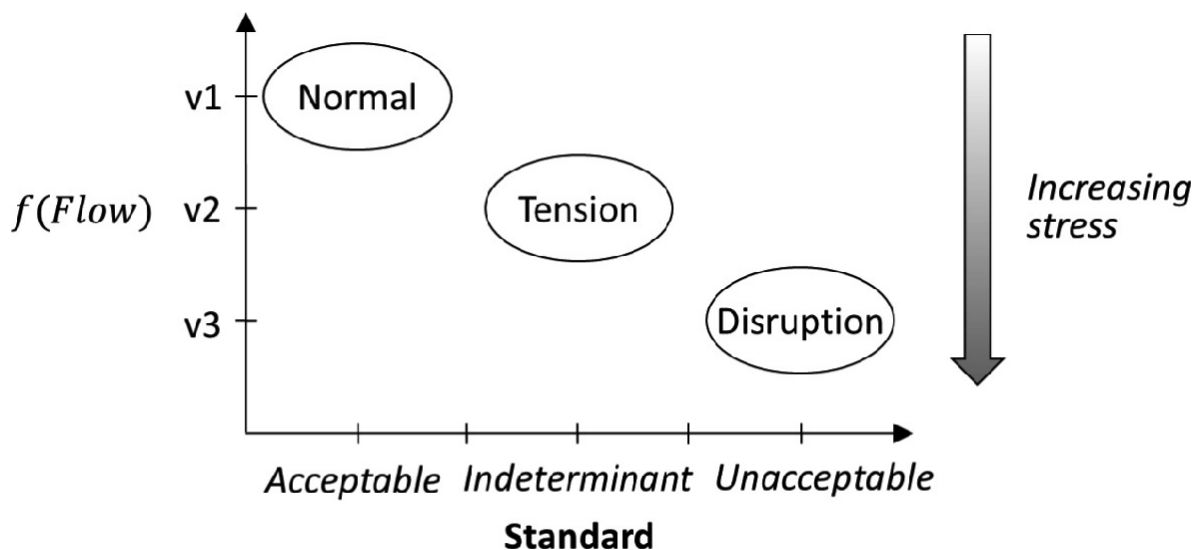


Fig. 8 Effects of acceptability events on stress

- Although it is possible to think of acceptability in binary terms (that is, an event is either acceptable or unacceptable, with no middle ground), in some situations there can be a third, intermediate level of acceptability, labeled as *indeterminant*. If necessary, indeterminant could be omitted entirely or divided further, although these would also be event-specific.
- An acceptability tipping point will be specific to the process and the event (the flow), occurring only when an

acceptable or indeterminant activity becomes unacceptable. Depending upon the process and the event, this can change over time as well.

- If the outcome of the event is acceptable, the process is considered to be in the Normal state, while indeterminant and unacceptable outcomes are associated with Tension and Disruptive states, respectively.
- A seemingly unrelated *Policy*_{IN} flow can lead to an acceptability event. The possible consequences of any *Policy*_{IN} flow must take into account its potential for causing another event, including those that can affect acceptability.

Acceptability events are often long term, affecting those living in jurisdictions worldwide. For example, World Health Organization global air quality guidelines for particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide [92], despite their health impacts making them unacceptable, are breached by many countries [93].

Sanctions against oil exporting countries with the aim of disrupting their economies because of activities deemed unacceptable is an example of a political acceptability event; for example, sanctions imposed by the United States on Iran, Venezuela, and Russia impact both the exporters and potential importers [11].

Whether an event is acceptable or unacceptable will depend on the event. A good example of this the phaseout of fossil fuels being called for by climate lobbyists and opposed by industrial lobbyists. At COP28 held in Dubai, the final communique was considered unacceptable by scientists and climate lobbyists [13], but was acceptable to oil industry lobbyists [101].

6 Event Tolerance

An event has no temporal component, it simply occurs and changes the stress associated with a process. However, the occurrence of an event and the time taken to recover from it are temporal and can be described using two methods associated with reliability [8]: Mean Time Between Failures (MTBF) and Mean Time to Recover (MTTR).

6.1 Mean Time Between Failures

Reliability refers to the ability of a system or component to function under stated conditions for a specified period of time [39]. MTBF is the mean (or average) time between failures of a component that is to be repaired and returned to service; it is the inverse of the failure rate, λ , the number of failures of the component over a period of time [21].³

As we are referring to the occurrences of events rather than failures (although a process might fail because of an event), we will use the abbreviation MTBE (Mean Time Between Events) rather than MTDF. Since an event causes a process to leave its Normal state, all references to MTBE will refer to the inability of a process to meet one or more of its indicators because of an event.

MTBE can be applied to any of the energy security indicators and their metrics. Each indicator, event, and metric value is described in Table 4. The MTBE of each can be calculated by determining the average of the number of occurrences of each event over a period (e.g., days, weeks, months, or years).

Table 4 Description of event occurrences

Indicator	Event description	Metric value
Availability	The available supply of energy in the $Energy_{IN}$ flow fails to meet the energy requirements of the $Demand_{OUT}$ flow	$\frac{Energy_{IN}}{Demand_{OUT}} < 1$

Indicator	Event description	Metric value
Affordability	The cost of $Energy_{IN}$ exceeds the budget for $Demand_{OUT}$	$\frac{Budget\ for\ Demand_{OUT}}{Cost\ of\ Energy_{IN}} < 1$
Acceptability	The $Energy_{OUT}$ flow exceeds the lower-limit (LL) of the standard in question	$f(Energy_{OUT}) > LL$

6.2 Mean Time to Recover

The mean time to recover (or repair) is the average time taken by those responsible for a process to return it to its Normal state after an event has occurred (i.e., the duration of the event). The recovery time can be dictated by the level of preparation for the event, the expected cost, and the perceived benefits [89]. As with MTBE, MTTR can be applied to the energy security indicators and metrics, as shown in Table 5; the average duration of the event can be determined from past experiences of the event.

Table 5 End-of-event descriptions

Indicator	End-of-event description	Metric value
Availability	The available supply of energy in the $Energy_{IN}$ flow is restored to meet the energy requirements of the $Demand_{OUT}$ flow	$\frac{Energy_{IN}}{Demand_{OUT}} \geq 1$
Affordability	The cost of $Energy_{IN}$ falls to a point where the budget for $Demand_{OUT}$ can meet the total cost	$\frac{Budget\ for\ Demand_{OUT}}{Cost\ of\ Energy_{IN}} \geq 1$
Acceptability	The $Energy_{IN}$ flow meets the lower-limit (LL) of the standard in question	$f(Energy_{IN}) \leq LL$

6.3 Tolerance

Ideally, events affecting a process would be rare or non-existent (i.e., $MTBE \rightarrow \infty$; that is, the value of MTBE is large and said to be approaching infinity). Resilient processes are designed to return to the Normal state quickly after the occurrence of an event (i.e., $MTTR \rightarrow 0$;

that is, the value of MTTR is small and said to be approaching zero). If the required changes to the processes are considered, for example, too costly or technically not feasible, certain events may be tolerated and dealt with as they occur (i.e., $0 < MTBE < \infty$ and $0 < MTTR < \infty$; here, the values of both MTBE and MTTR fall between 0 and infinity and are considered tolerable).

In certain cases, the frequency of an event's occurrence or the time taken to recover, or both, becomes intolerable (i.e., $MTBE \rightarrow 0$ and $MTTR \rightarrow \infty$) and may result in the processes affected by the event adapting to a new Normal state. In the new Normal state either the event has limited (or negligible) effects on the operation of the process (i.e., $MTBE \rightarrow \infty$) or process is resilient to the event (i.e., $MTTR \rightarrow 0$).

The different combinations of MTBE and MTTR are summarized in Table 6.

Table 6 Summary of the different combinations of MTBE and MTTR

MTBE Time between events...	MTTR Time to recover...		
	$\rightarrow 0$ Instant or very rapid	$> 0 \dots < \infty$ Tolerable	$\rightarrow \infty$ Intolerably long or no recovery
$\rightarrow 0$ Continuous or intolerably frequent	Intolerable	Intolerable	Intolerable
$> 0 \dots < \infty$ Tolerable	Tolerable (Resilient)	Tolerable	Intolerable
$\rightarrow \infty$ Very rare or no events	Tolerable (Resilient)	Tolerable	Intolerable

Although the tolerance of an event can be subjective and vary between processes, Table 7 enumerates and describes the limits of a process's tolerance and possible reasons for it to adapt to a new Normal state.

Table 7 Limits to a process's tolerance

MTBE	MTTR	Description
Tolerable	Tolerable	The occurrence of the event is considered tolerable; when it occurs, the recovery time is also considered tolerable. There is little incentive for adaptation
Tolerable	Intolerable	The occurrence of the event is considered tolerable; however, the time taken to recover (i.e., MTTR or the duration of the event) is considered intolerable, which may result in adaptation
Intolerable	Tolerable	The time between events is considered intolerable, but the time required to rectify them is considered tolerable. This may result in adaptation since MTBE is considered intolerable
Intolerable	Intolerable	Both the time between events and the time taken to rectify them are considered intolerable. There is a strong incentive for adaptation

6.4 Examples

MTBE and MTTR are essential aspects of energy system design; allowing for the design and implementation of safe and reliable systems. Examples of their use, both explicitly and implicitly, include:

- The demand for home photovoltaic (PV) systems in many countries has increased sharply over the past decade. Many systems are installed under the assumption that they require no maintenance, which can lead to catastrophic failure, especially for users of off-grid systems. In the U.K. grid-connected PV systems must carry out quarterly inspections to check for component failure (initial failures, random failures, and end-of-life failures) if they are to qualify for feed-in tariffs. In [61], the authors describe how the risks to energy output of

household PV systems are measured using MTBF and MTTR.

- The performance of electricity systems is essential to both electricity providers and end users. Two performance indicators, SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index), can be used to measure the interruption durations and interruption frequencies to the end users served per year [79], where (CHI is customer-hours of interruption or the number of customers $\times$ duration of interruption; CI is the number of customer interrupts or the total number of customers interrupted; and TCS is the total number of customers served in the system) [20]:

$$SAIFI = \frac{\sum CHI}{TCS} \quad SAIDI = \frac{\sum CI}{TCS}$$

SAIFI and SAIDI correspond to MTBE and MTTR, respectively. They can be used by regulators to set electricity provider standards [71].

- Two of the concerns often expressed by potential purchasers of electric vehicles (EVs) are charging (the availability of infrastructure and charging time) and vehicle range [22, 41, 102]. These are equivalent to MTTR (the time taken to recharge the battery) and MTBE (where the event is a low battery charge). Both vehicle and EVSE (Electric Vehicle Supply Equipment) manufacturers have responded to MTTR by designing vehicles and EVSE to charge at higher power levels, increasing the voltage and using DC rather than AC, ensuring a faster charge. Jurisdictions wanting more EVs on the road are increasing the availability of charging infrastructure [28]. Although most EV battery sizes are adequate to meet drivers' travel needs [74], "range anxiety" or MTBE is still a barrier to some drivers, often

those living in colder climates [44]. Manufacturers have responded with larger battery capacity allowing a greater range [82].

7 Resilient Systems and Processes

Resilience can be defined as the “ability to recover quickly from illness, change, or misfortune” [80]. Using this definition, a resilient process can be described as one that after an event that changes an indicator has occurred, employs actions or *countermeasures* to return to its Normal state by reducing its current level of stress quickly; the interpretation of “quickly” depends on the process affected by the event.

For a resilient process to reduce its stress levels and return to its Normal state after an event, it must be designed to handle the event whenever it occurs (i.e., its countermeasures). Once in the Normal state, the indicators signal that all flows have been restored.

Resilience can refer to the time taken to recover from an event (i.e., MTTR) or how often it occurs (i.e., MTBE), or a combination of both. The percentage of time a process is not affected by an event is shown in the following equation, increasing as $MTTR \rightarrow 0$ and decreasing as $MTTR \rightarrow \infty$ [62]:

$$\frac{MTBE}{MTBE + MTTR}$$

After an event, a process that is unable to return to its Normal state in a timely manner might consider the situation intolerable. To be considered resilient, the combination of MTTR and MTBE must be tolerable.

A resilient process or system is one that has been designed to either withstand specific events or, if an event occurs putting the process into either the Tension or Disruption state, it must be able to return to its Normal

state within a tolerable period to bring its stress level to zero. If a process in the Disruption state has its stress reduced to below the tipping point, but still not zero, it can enter the Tension state. However, to be considered resilient, the process must return to its Normal state. The three states and the conditions for leaving them are shown in Fig. 9.

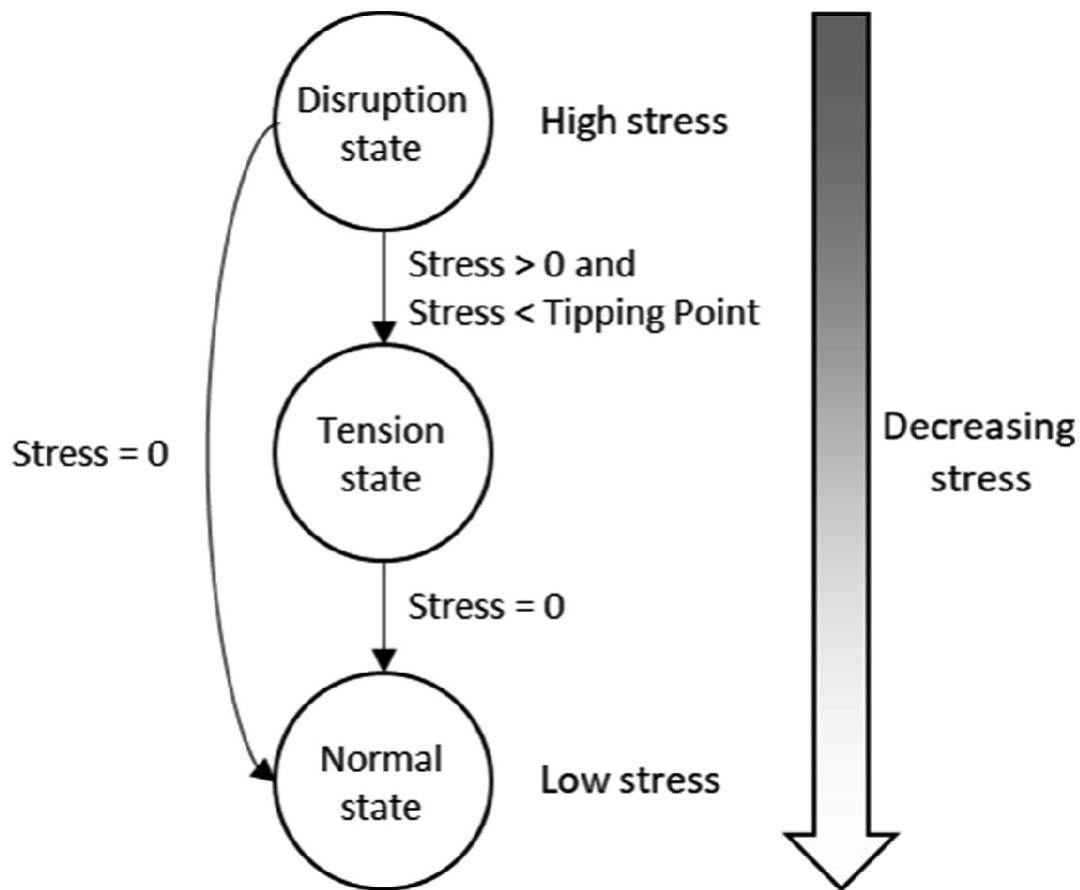


Fig. 9 The resiliency state diagram

A process is in a Normal state when the flows associated with the three energy security indicators (availability, affordability, and acceptability) are meeting their requirements. Returning the process to its Normal state within a tolerable period is essential if the process (and ultimately the energy system) is to be considered resilient.

Loss of availability can be the result of an upstream process being unable to meet the process's $Demand_{OUT}$.

For the process to remain resilient, it is the responsibility of the upstream process to resume the *Energy_{IN}* flow within a tolerable period. Failure to do so will require the process to adapt to a new Normal.

Loss of affordability requires the process to find additional funds if it is to afford its *Energy_{IN}*. This can be achieved at the expense of other budgets available to the process or to obtain external support from an organization. Alternatively, the process will need to adapt to the new Normal of higher energy costs.

If the *Energy_{IN}* flow is deemed unacceptable, the process will need to decide what actions to take. Ideally, the event is short term and the process can resume with an acceptable *Energy_{IN}* flow. However, as with the other indicators, if the event becomes intolerable, the process will need to adapt to its new Normal.

8 Adaptation

If the stress of an event becomes intolerable to the process and the process is unable to function as required, new, effective countermeasures must be developed so the process can become resilient to the new event.

The steps involved in moving a process from its Disruption state (assumed to be intolerable) to one that is tolerable is referred to as an *adaptation*. This becomes the process's new Normal state (Fig. 10). In the new Normal state, the process is resilient to both the new event and the events to which it was previously resilient.

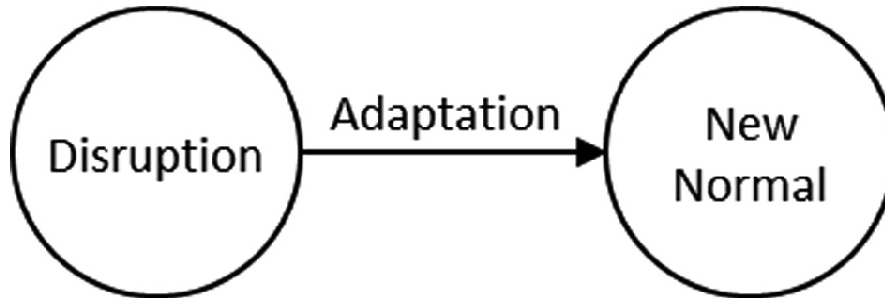


Fig. 10 Adapting to the new normal

Adaptation in an energy system can be achieved in one of three ways, referred to as the three 'R's.

8.1 The Three 'R's

If a process or a group of processes in an energy system enter, or might enter, their respective Disruptions states, the organizations responsible for the processes can develop policy responses to adapt the processes to their new Normal. This improves the resilience of the processes and the energy system. The success of an energy policy can be measured with the indicators described in Sect. 3.1.

Regardless of the indicator, the indicator values are the result of a process expecting to meet its $Demand_{OUT}$ with available or affordable, or both, supplies of $Energy_{IN}$. The success of a process maintaining or improving its resilience ultimately requires an organization (such as an institution, corporation, or government) to develop and implement energy policies to meet this goal. These are the $Policy_{IN}$ flows shown in Fig. 2.

Policies are not considered to be measurable; however, the outcomes of policies are measurable and can be reflected in one or more of a process's output flows, $Demand_{OUT}$, $Environment_{OUT}$, and $Energy_{OUT}$, and $Demand_{IN}$. For a policy to have improved the process's energy security, at least one of the indicators associated with a flow's characteristic must have improved as well.

In [32], it was shown that energy policies could be discussed in terms of their potential to reduce an output flow, replace an input flow or the process itself, and restructure the process and input flows. While such policies can affect the $Energy_{OUT}$ and $Environment_{OUT}$ flows, it is the process and the $Energy_{IN}$ flow that ultimately undergo the change. The relationship between the policies, the process, and $Energy_{IN}$ is shown in Table 8. For example, if a policy results in a new process and a new $Energy_{IN}$, it is a restructuring; whereas a new process using an existing $Energy_{IN}$ is a replacement (note there are two approaches to replacement, either the process or $Energy_{IN}$ are changed, not both).

Table 8 The relationship between policies, the process, and the type of $Energy_{IN}$

Type of $Energy_{IN}$	Process	
	Unchanged	New
Unchanged	Reduction	Replacement
New	Replacement	Restructuring

A detailed description of each type of policy and how it can influence the characteristics of different flows now follows.

8.1.1 Reduction

Reduction policies are intended to reduce one or more of a process's $Demand_{OUT}$, $Environment_{OUT}$, or $Environment_{IN}$ flows in response to event that:

- Causes the availability, affordability, or acceptability of an $Energy_{IN}$ flow to decline. The process can respond by reducing its $Demand_{OUT}$ flow, thereby reducing its

$Energy_{IN}$ flow and, ideally, its impact on the environment flows.

- Decreases the acceptability of either the $Environment_{IN}$ or $Environment_{OUT}$ flow.

Since neither the process nor the type of energy associated with $Energy_{IN}$ is changed, a reduction policy must change how the process uses its energy. This can be achieved through conservation or energy efficiency measures.

Conservation measures

A conservation measure is a short-term action that temporarily reduces $Demand_{OUT}$. Examples include reducing the use of an automobile because of rising fuel costs or a shortage caused by energy rationing [30]. When the event requiring the temporary reduction in $Demand_{OUT}$ stops, the process can return to its previous normal; for example, increasing the use of an automobile because fuel costs decline or rationing stops.

Energy efficiency measures

Energy efficiency measures are long-term actions intended to permanently reduce $Demand_{OUT}$, possibly improving affordability and acceptability. Examples include:

- Tuning an automobile engine (to reduce its energy demand), removing unnecessary items from the automobile (to reduce weight), and to ensure that tires are properly inflated (to reduce fuel consumption) [67].
- Retrofitting older homes with insulation is an energy efficiency measure that can significantly reduce household energy demand without changing either the energy source or the heating system (i.e., the process)

[91]. There can be health benefits (i.e., acceptability), including reduced hospital visits and fewer days off work and school [16].

- In hot weather, the set point of an air conditioner can be raised to reduce the demand for electricity [78], while the lower and upper thermostats on a water heater can be adjusted to improve efficiency and reduce electricity demand [43].
- In households using natural gas furnaces for heating, adjusting the flue damper angle on the furnace can improve furnace efficiency and in doing so, reduce emissions [47].

There can be unintended events to a reduction measure. For example, by reducing consumption of $Energy_{IN}$, the affordability can improve in that the process uses less energy and hence pays less; however, the benefits associated with such actions can be short-lived if the upstream process (the source of $Energy_{IN}$) is forced to increase the cost of the $Energy_{OUT}$ flow to cover expenses caused by, for example, stranded assets [29].

Some jurisdictions create explicit reduction policies to discourage or modify the use of a particular process or an $Energy_{IN}$ flow. Such policies often impose taxes on the $Energy_{OUT}$ flow to increase its cost thereby decreasing its affordability and discouraging its consumption. Carbon taxes on the consumption of a specific type of fuel to improve the acceptability of the $Environment_{OUT}$ flow is an example of such a policy [42].

All the above actions are in response to an event. They change neither type of $Energy_{IN}$ nor the process.

8.1.2 Replacement

A replacement policy is one that changes either the process or one or more of its $Energy_{IN}$ flows, but not both. The

output energy flow ($Energy_{OUT}$) for a downstream process or end-use service remains unchanged. If a process is replaced, it must continue to use the same $Energy_{IN}$, ideally there will be a decline in its consumption leading to an improvement in one or more of the indicators. If a replacement $Energy_{IN}$ flow is introduced, it must be compatible with the previous $Energy_{IN}$ to allow the process to continue operating; the success of the flow (i.e., any increase in energy security) is detected in one or more of the process's other indicators.

Examples of a process replacement, keeping the same $Energy_{IN}$, include:

- Underground storage tanks can rust and leak without proper protection, potentially affecting groundwater supplies [58]. This is an acceptability issue. A common solution is to remove the product and replace the storage tank with one that is not prone to corrosion, such as reinforced fiberglass [69]. This is a replacement because the same type of energy is being stored.
- Low-efficiency thermal power stations using coal can be replaced with supercritical (coal) generation, increasing electrical production ($Energy_{OUT}$) without increasing emissions ($Environment_{OUT}$) [97].
- All-electric boilers and resistive baseboard heaters heat can be replaced with an (electric) air-sourced heat pump. Since air-sourced heat pumps are more efficient than electric boilers and resistive heaters, the operating costs and indirect emissions are lower, improving both affordability and acceptability, respectively [46].
- An internal combustion engine (ICE) vehicle can be replaced with a hybrid electric vehicle (HEV) since both use gasoline. However, HEV's use electric powertrains and regenerative braking, making them more efficient ICEs, lowering operating costs and emissions [4].

- Incandescent bulbs can be replaced with light emitting diode bulbs since both use electricity.

Examples of replacing an $Energy_{IN}$ and keeping the process unchanged include:

- Flex-fuel vehicles can operate with various combinations of ethanol and gasoline, usually in the range of 10% ethanol (E10) to 85% ethanol (E85) [54]. Fueling with E85 rather than E10 is an example of a replacement [5].
- A thermal power station has a heat source, such as coal, which produces steam in boiler to power a steam turbine for electricity generation. By replacing the heat source (coal) with an SMR (small modular nuclear reactor), to produce steam, the same process (that is, the steam turbine) could be used, thereby reducing construction costs [49].
- In the early part of the nineteenth century, whale oil lamps were the source of illumination in many households in the eastern United States. Kerosene replaced whale oil as whale populations were declining in the mid-1800s; whale oil lamps were used with kerosene [73].

Replacement decisions can affect any of the three indicators.

8.1.3 Restructuring

Unlike a replacement, restructuring changes *both* the energy ($Energy_{IN}$) and the new process that uses the energy. The new process's $Energy_{OUT}$ remains the same. The restructuring is intended to reduce the stress on any downstream processes or energy services using its $Energy_{OUT}$. Examples of restructuring include:

- A personal transportation system relying on an existing gasoline powered vehicle with an internal combustion

engine could be restructured to use a plug-in battery electric vehicle powered by electricity [88]. The energy service, transporting goods or people, remains the same. The reason for the restructuring is often one of affordability; for example, a carbon tax on gasoline increasing its cost [12]. If electric vehicle prices are reduced by through subsidies, the affordability of the vehicles might make them a more attractive option to potential buyers [40].

- If a household relying on a furnace using fuel oil needs to replace the system, it might be less expensive to restructure the system with a heat pump using electricity. The heat pump might be as expensive as a new oil furnace, but since the heat pump is typically more efficient than a furnace and if the cost of electricity is less than the cost of fuel oil, the restructuring could be an affordability issue [55]. In some situations, continuing to use heating oil could be an acceptability issue because oil storage tanks can rust [94] allowing the oil to leak and resulting in costly restoration of the oil-soaked ground [59].
- In the 1970s, the oil embargos against western countries created availability and affordability issues. Japan, which relied on previously low-cost bunker oils for electricity generation, began to restructure their electricity production away from bunker oil to nuclear power [48].
- The restructuring of much of the electricity system from coal to natural gas in the United States is the result of the low cost of lower-emission natural gas and renewables [19].
- Individual households and small enterprises affected by electricity blackouts often restructure their energy system so that the loss of grid-supplied electricity is replaced with their own generators operating on gasoline or propane [24]. This can lead to acceptability stresses to

the household or other households because of noise and air emissions from the generators [15].

Restructuring is not restricted to existing processes. If new processes are added to the system (such as the addition of storage [2]), requiring new energy flows or changes to existing flows, this is also a restructuring of the energy system.

9 Discussion

A resilient energy system is one that ensures its end users receive the energy they require at an affordable price. The energy available for use must also be considered acceptable, meeting certain standards. A resilient energy system is one that is energy secure. However, if an event occurs that disrupts the end user's supply of energy or makes it unaffordable or unacceptable, and the system is unable to recover, it must adapt to its new state. Resilience is an essential attribute for any energy system.

9.1 When to Adapt

An energy system is resilient when the energy demands of its energy services are met by energy flows that are available, affordable, and acceptable. Maintaining or improving an energy system requires those responsible for the system's processes to adopt measures that ensure their resilience when an event takes place. However, if an event occurs for which a process is not considered resilient, because either the time between events (MTBF) is too short or the time to recover from the event (MTTR) is too long, or both, the system can no longer be considered resilient because the associated stresses increase. In these situations, reduction, replacement, or restriction policies need to be implemented ex-post to adapt the process to the new Normal so that it and the system remain resilient should the event recur.

A process can adapt to an event after the event has occurred (ex-post); in these cases, those responsible for the process follow the generic flowchart shown in Fig. 11. The flowchart begins with the symbol labeled “Ex-post event” and ends with the process resuming (symbol labeled “Resume process”). If both MTBF and MTTR are tolerable, or functioning with the loss of either is considered tolerable, the process is resilient with respect to the event. However, if both MTBF and MTTR are intolerable or the loss of either is considered intolerable, new policy is required to adapt the process to the event (the steps associated with determining the policy for the event are described below).

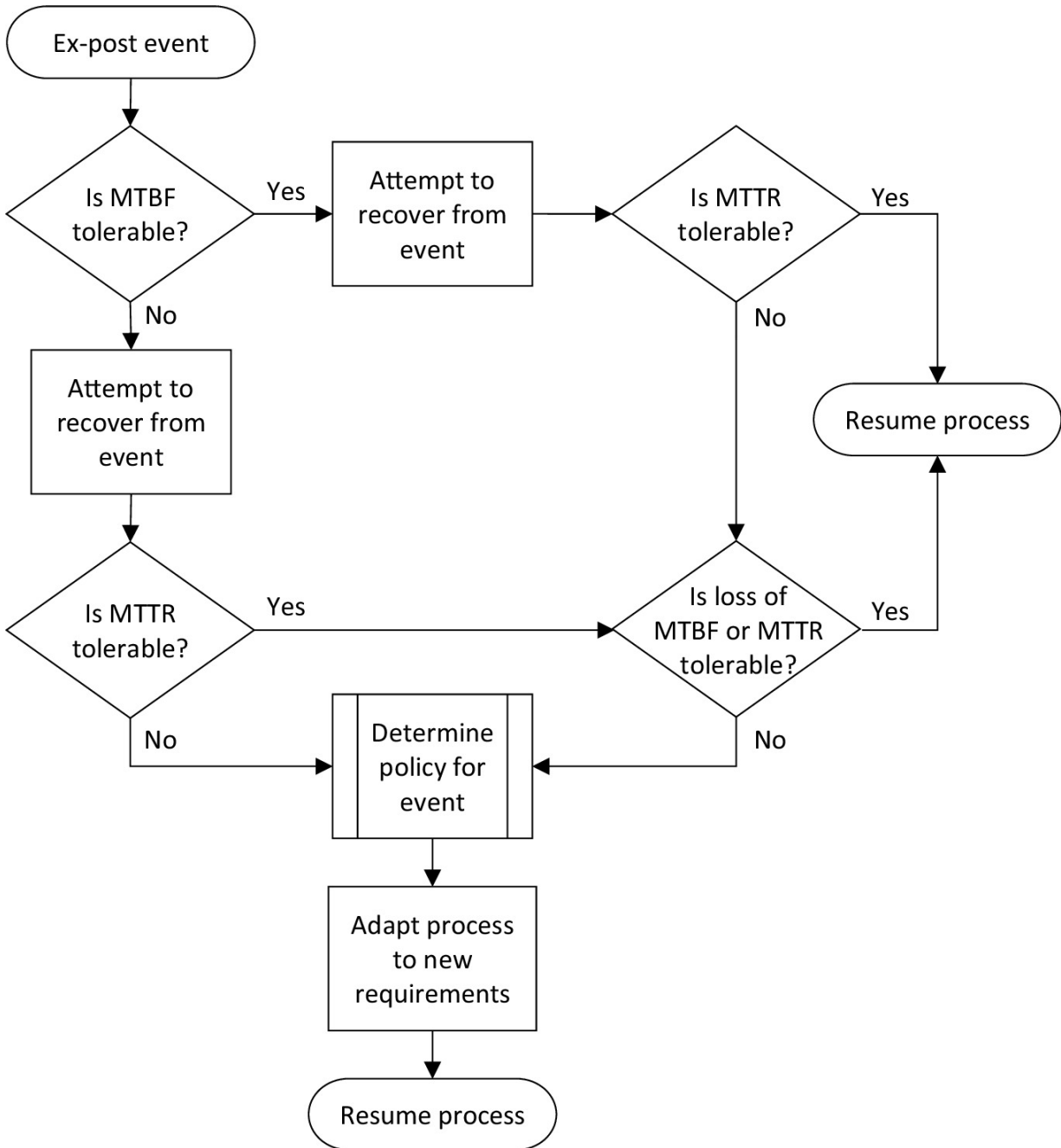


Fig. 11 Flowchart of ex-post decisions and actions [34]

Alternatively, those responsible for the process can conduct periodic reviews of its resilience and consider the likelihood of the effects of the occurrence of different events before they occur (ex-ante), such as the Integrated Resource Plans conducted by governments and electricity suppliers [14]. Figure 12 is a generic flowchart of the steps taken to determine the effects of an event on a process,

beginning with a simulation of the event on the process and then determining the probable MTBF and MTTR. If the event is not tolerable and its associated risk is considered high, it is necessary to adapt to the event by creating new policy for the process (the steps associated with determining the policy for the event are discussed below); this new policy can be applied to the process and the steps can be repeated starting with the simulation of the event on the “new” process. If the event is considered tolerable or intolerable with a low risk, the process is either resilient (if it was not adapted) or must be adapted (if the event required adaptation). The simulation of the event on the process can also be applied in ex-post events.

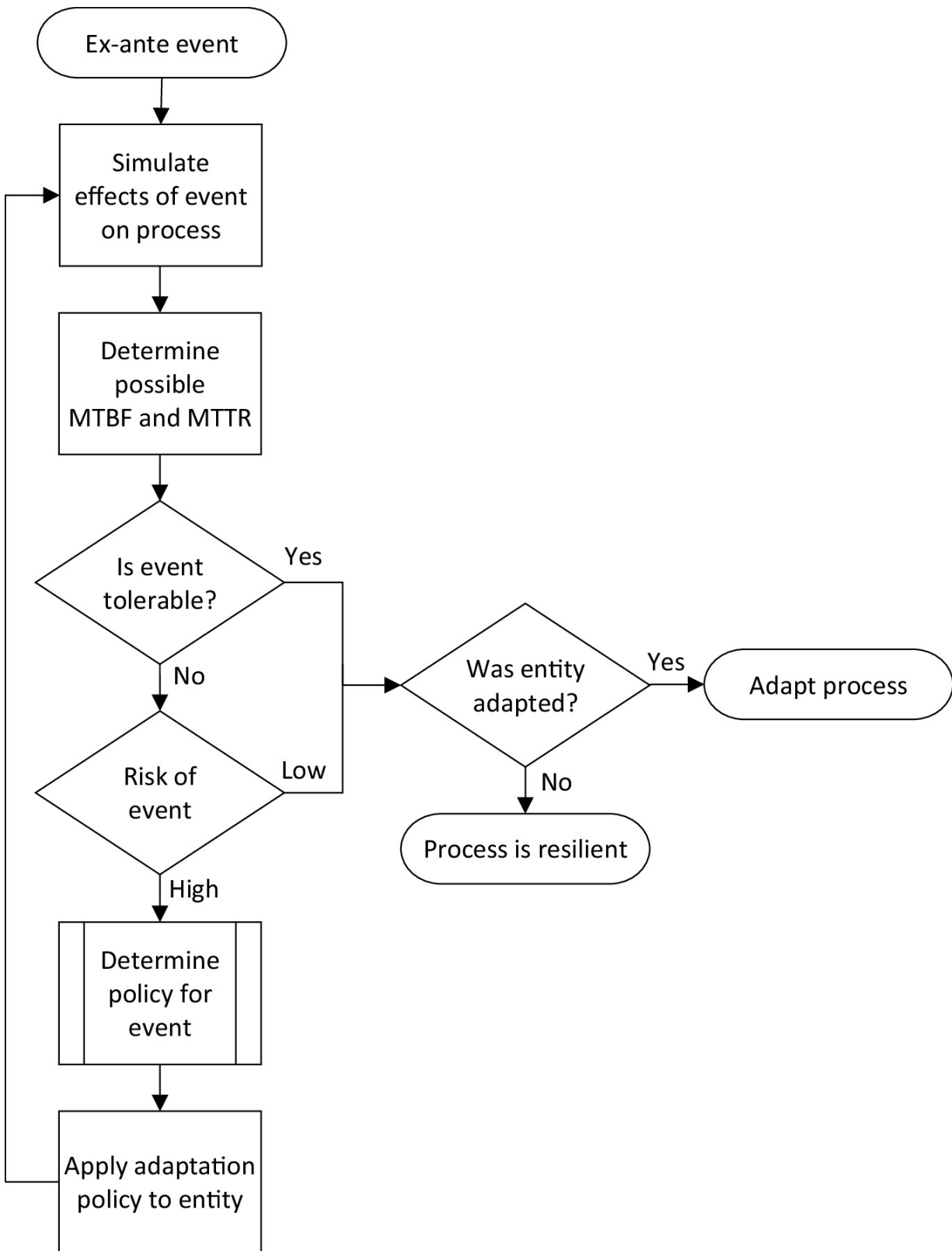


Fig. 12 Flowchart of ex-ante decisions and actions [34]

If a process is to be adapted to an event, it is necessary for those responsible for the process to determine the policy or requirements for it to become resilient to the event and then apply the necessary changes to adapt the process to its new Normal. The following describes a set of generic steps that can be employed when determining a policy to handle an event:

- (1) Develop reduction policies for the event
- (2) Develop replacement policies for the event
- (3) Develop restriction policies for the event
- (4) Compare the costs, benefits, and possible impacts on other processes (both upstream and downstream) of each policy (from steps 1 through 3)
- (5) Select the best policy from the different policies (from step 4).

9.2 Policy Notes

The three fundamental characteristics of any system are hierarchy, resilience, and reorganization [53]. Not surprisingly, these characteristics are found in an energy system: hierarchy (energy flows increase in entropy as they move from source to service through the system's internal processes), resilience (processes respond to events in a timely, tolerable fashion to return to the Normal state), and reorganization (processes are adapted to become resilient to intolerable events). Understanding these characteristics is essential when developing energy policy to ensure the resilience of a jurisdiction's energy system and its processes.

9.2.1 Unintended Consequences

Ideally, any policy decision taken to reduce the stress on a process should do so; however, in some cases, the policy can have unintended consequences, three of which are considered here.

The rebound effect occurs when a policy applied to a process improves the affordability of its $Energy_{OUT}$ flow (such as reduction policies that decrease the flow's energy intensity), thereby reducing the cost of the flow to the downstream processes (i.e., processes or external entities) that consume it [10]. If the improved affordability causes these processes to increase their demand for the flow, the additional demand may impact the availability of the flow (direct rebound). Should any savings made be parlayed into new or additional demand for a different $Energy_{OUT}$ flow, this new demand could prove detrimental to the security of the second flow (indirect rebound).

Policies that cause a decline in the $Demand_{OUT}$ of a process can affect the processes or terminators responsible for the $Energy_{IN}$ flow as they might find it difficult or impossible to supply the energy because of reduced revenues. Take-or-pay contracts are one way to protect the suppliers of the $Energy_{IN}$ flow [96]; however, such contracts will not improve the affordability of the energy flow unless the contract is renegotiated.

Improving a system's $Environment_{OUT}$ flow by increasing the use of variable sources of electricity such as wind can have other repercussions since ensuring the availability of on-demand electricity requires backup sources of electricity. If the backup source is carbon intensive, the anticipated improvements in the environmental acceptability might not be realized; similarly, any expected improvements in affordability could be offset by the costs associated with the backup source.

9.2.2 The Effectiveness of a Policy

The effectiveness of a policy is determined by the degree to which it reduces the stress on a process and improves the jurisdiction's energy security. When an individual takes an action that affects the energy security of a particular energy service, the effect on the overall energy system is probably minor —although to the individual, its effect may be significant. At the other extreme, the larger the number of processes affected by a policy, the greater the impact on system. This means it is not the type of policy (i.e., reduction, replacement, or restriction) that determines its contribution to the energy security of the energy system, but rather the extent to which it improves the overall energy security of the energy chain or energy system, or both.

10 Summary

This chapter has taken a systems approach to explaining how resilience can be maintained through adaptation in an energy system.

We began by describing how an energy system can be represented by three types of process: conversion processes, for converting a primary energy source into a secondary energy source; transfer processes, transporting a primary or secondary source from one location to another; and storage processes, which store primary or secondary energy until it is required by the end-user.

All processes have the same basic structure, they take a supply of energy and supply it to meet the demand of another process or an end-user. Processes are governed by rules set by governments, corporations, and manufacturers. Processes also interact with their environment, potentially affecting those living in it.

We can use the flows between processes (such as requests for, and supplies of, energy) to determine the state of the system. The state of the flows can represent the energy security of a system or a process by measuring any or all of the three indicators: the availability, affordability, and acceptability of an energy flow. Ideally, an energy supply (represented by a flow) is available, affordable, and acceptable, ensuring the end-user with a supply of energy for a sector or a service. This is the Normal state of a process or an end-user.

However, if an event occurs that changes any of flows associated with these indicators there can be an increase on the stress on the system's processes (i.e., processes or the end-user's requirements, or both). We can measure or estimate the stress of an individual event by comparing the actual flow with the expected or required flow. In addition, the stress on the process is affected by how often the event occurs (the meantime between events) and how long it takes to recover from the event (the meantime to recover).

Ideally, the process has countermeasures in place to minimize the degree of stress caused by the event, making the event tolerable. If the event cannot be handled but the process can still function, it enters the Tension state, making it less tolerable. In the most extreme case, the stress is intolerable and the process enters into a Disruption state. In both cases, the process needs to return to its Normal state if it is to function as required; this can be done by reducing the stress caused by the event. If those responsible for the process can return it to the Normal state from either the Tension or Disruption states, the process is said to be resilient.

In some situations, those responsible for the process are unable to return it from the Disruption state to the Normal state. When this occurs, the disrupted process or downstream processes relying on its flows must look for a new Normal state. Entering a new Normal can be done in

one of four ways. First, the process can take actions to reduce its energy demand. Second, an existing $Energy_{IN}$ flow can be replaced with one that is more reliable. Third, if the process itself is the source of the stress, it could be replaced with one that is more reliable and uses the same $Energy_{IN}$. Fourth, in the most extreme case, both the process and its $Energy_{IN}$ flows can be replaced; this requires the new process's $Energy_{OUT}$ flow or service, must be identical to that of the original process and its energy sources. When a process enters a new Normal state, an adaptation is said to have occurred.

In its new Normal state, the process should be resilient to both the new event and the previous events that it had countermeasures in place to handle.

Any system must be resilient if it is to handle known events. When confronted with a new event for which it is unprepared, the system must be able to adapt to the event if it is to be useful to the external entities that rely on it.

In any energy system, this means being able to reduce, replace, and restructure.

References

1. AHD (2011) American heritage dictionary of the english language, Fifth edn. Houghton Mifflin Company. Retrieved 16 Jan 2023, from <https://www.thefreedictionary.com/system>
2. Albertus P, Manser JS, Litzelman S (2020) Long-duration electricity storage applications, economics, and technologies. *Joule* 4:21–32. Retrieved from [https://www.cell.com/joule/pdf/S2542-4351\(19\)30539-2.pdf](https://www.cell.com/joule/pdf/S2542-4351(19)30539-2.pdf)
3. Anwar MN, Shabbir M, Tahir E, Iftikhar M, Saif H, Tahir A, Murtaza MA, Khokhar MF, Rehan M, Aghbashlo M, Tabatabaei M, Nizami A-S (2021) Emerging challenges of air pollution and particulate matter in China, India, and Pakistan and mitigating solutions. *J Hazard Mater* 416. <https://doi.org/10.1016/j.jhazmat.2021.125851>

4. Asfoor MS, Sharaf AM, Beyerlein S (2014) Use of GT-suite to study performance differences between internal combustion engine (ICE) and hybrid electric vehicle (HEV) powertrains. In: 16th International Conference on Applied Mechanics and Mechanical Engineering. A.M.M.E., Cairo, pp 19–34. Retrieved from https://amme.journals.ekb.eg/article_35473_db00a02944c5d1d825b4662eb2dd79f6.pdf
5. Azhaganathan G, Bragadeshwaran A (2022) Critical review on recent progress of ethanol fuelled flex-fuel engine characteristics. *Int J Energy Res* 46(5):5646–5677. <https://doi.org/10.1002/er.7610>
6. Banfi S, Filippini M, Mueller A (2005) An estimation of the Swiss hydropower rent. *Energy Policy* 33(7):927–937. <https://doi.org/10.1016/j.enpol.2003.10.015>
7. Belmecheri S, Babst F, Wahl ER, Stahle DW, Trouet V (2015) Multi-century evaluation of Sierra Nevada snowpack. *Nat Clim Change* 6(2–3). <https://doi.org/10.1038/nclimate2809>
8. Blanchard B, Lowery E (1969) *Maintainability: principles and practices*. McGraw-Hill
9. Brand MA, Muñiz GI, Quirino WF, Brito JO (2011) Storage as a tool to improve wood fuel quality. *Biomass Bioenergy* 35(7):2581–2588. <https://doi.org/10.1016/j.biombioe.2011.02.005>
10. Brockway PE, Sorrell S, Semieniuk G, Heun MK, Court V (2021) Energy efficiency and economy-wide rebound effects: a review of the evidence and its implications. *Renew Sustain Energy Rev*. <https://doi.org/10.1016/j.rser.2021.110781>
11. Brown P (2020) Oil market effects from U.S. economic sanctions: Iran, Russia, Venezuela. Congressional Research Service, Washington. https://www.everycrsreport.com/files/20200205_R46213_7bb76e54df206bce64dd8b2f4b4c8543148720df.pdf
12. Canada (2023) Fuel charge rates. Retrieved from Canada Revenue Agency: <https://www.canada.ca/en/revenue-agency/services/forms-publications/publications/fcrates/fuel-charge-rates.html>
13. Carrington D (2023) Failure of Cop28 on fossil fuel phase-out is ‘devastating’, say scientists. Retrieved from The Guardian: <https://www.theguardian.com/environment/2023/dec/14/failure-cop28-fossil-fuel-phase-out-devastating-say-scientists>
14. Carvallo JP, Larsen PH, Sanstad AH, Goldman CA (2018) Long term load forecasting accuracy in electric utility integrated resource planning. *Energy Policy* 119:410–422. <https://doi.org/10.1016/j.enpol.2018.04.060>

- [Crossref]
15. Casey JA, Fukurai M, Hernández D, Balsari S, Kiang MV (2020) Power outages and community health: a narrative review. *Curr Environ Health Rep* 7:371–383. <https://doi.org/10.1007/s40572-020-00295-0> [Crossref]
 16. Chapman R, Howden-Chapman P, Viggers H, O’Dea D, Kennedy M (2009) Retrofitting houses with insulation: a cost-benefit analysis of a randomised community trial. *J Epidemiol Community Health* 63(4):271–277. <https://doi.org/10.1136/jech.2007.070037> [Crossref]
 17. Colgan JD, Gard-Murray AS, Hinthorn M (2023) Quantifying the value of energy security: How Russia's invasion of Ukraine exploded Europe's fossil fuel costs. *Energy Res Soc Sci* 103. <https://doi.org/10.1016/j.erss.2023.103201>
 18. Devi S, Mehta M (2021) Usage pattern and work profile in dung collection among rural women. *Int J Adv Educ Res* 6(4):7–13. Retrieved 25 Mar 2024, from <https://multidisciplinaryjournals.org/assets/archives/2021/vol6issue4/5-5-16-118.pdf>
 19. EIA (2019) Short-term energy outlook. Retrieved 14 Feb 2019, from U.S. Energy Information Administration: https://www.eia.gov/outlooks/steo/pdf/steo_full.pdf
 20. Electricity Canada (2022) Transmission & distribution indicators. Retrieved from Electricity Canada: <https://www.electricity.ca/knowledge-centre/the-grid/distribution/transmission-distribution-indicators/>
 21. EPSMA (2005) Reliability—guidelines to understanding reliability prediction. European Power Supply Manufacturers Association. Retrieved from www.epsma.org
 22. Featherman M, Jia S, Califf CB, Hajli N (2021) The impact of new technologies on consumers beliefs: Reducing the perceived risks of electric vehicle adoption. *Technol Forecast Soc Change*. <https://doi.org/10.1016/j.techfore.2021.120847>
 23. Fernández IA, Gómez MR, Gómez JR, Insua ÁB (2017) Review of propulsion systems on LNG carriers. *Renew Sustain Energy Rev* 67:1395–1411. <https://doi.org/10.1016/j.rser.2016.09.095> [Crossref]
 24. Ghanem DA, Mander S, Gough C (2016) “I think we need to get a better generator”: household resilience to disruption to power supply during storm events. *Energy Policy* 92:171–180. <https://doi.org/10.1016/j.enpol.2016.02.003>

- [Crossref]
25. González-Eguino M (2015) Energy poverty: an overview. *Renew Sustain Energy Rev* 47:377–385. <https://doi.org/10.1016/j.rser.2015.03.013> [Crossref]
 26. Gustafsson, S.-I., & Karlsson, B. G. (1992, December). Heat accumulators in CHP networks. *Energy Conversion and Management*, 33(12), pp. 1051–1061. [https://doi.org/10.1016/0196-8904\(92\)90002-E](https://doi.org/10.1016/0196-8904(92)90002-E)
 27. Halko, G. E., & Gkampoura, E.-C. (2021, July). Evaluating the effect of economic crisis on energy poverty in Europe. *Renewable and Sustainable Energy Reviews*, 144. <https://doi.org/10.1016/j.rser.2021.110981>
 28. Hall D, Lutsey N (2020) Electric vehicle charging guide for cities. International Council on Clean Transportation, Washington, DC. Retrieved from https://energypedia.info/images/5/57/030_Electric_vehicle_charging_guide_for_cities_.pdf
 29. Hansen T (2022) Stranded assets and reduced profits: analyzing the economic underpinnings of the fossil fuel industry's resistance to climate stabilization. *Renew Sustain Energy Rev* 122. <https://doi.org/10.1016/j.rser.2022.112144>
 30. Heggie A, Eager D, McKinnon K, Van Der Weijde AH (2018) Power rationing in a long-term power shortage. *Energy Policy* 121:202–210. <https://doi.org/10.1016/j.enpol.2018.06.025>
 31. Howari, F. (2015). Evaporation losses and dispersion of volatile organic compounds from tank farms. *Environmental Monitoring Assessment*, 187(273). <https://doi.org/10.1007/s10661-015-4456-z>
 32. Hughes L (2009) The four 'R's of energy security. *Energy Policy* 37(6):2459–2461
 33. Hughes L (2012) A generic framework for the description and analysis of energy security in an energy system. *Energy Policy*, pp 221–231. <https://doi.org/10.1016/j.enpol.2011.11.079>
 34. Hughes L (2015) The effects of event occurrence and duration on resilience and adaptation in energy systems. *Energy* 84:443–454. <https://doi.org/10.1016/j.energy.2015.03.010> [Crossref]
 35. Hughes L, Ranjan A (2013) Event-related stresses in energy systems and their effects on energy security. *Energy* 59:413–421. <https://doi.org/10.1016/j.energy.2013.06.070> [Crossref]

36. IEA (2010) Energy security. Retrieved 27 Dec 2010, from International Energy Agency: http://www.iea.org/subjectqueries/keyresult.asp?KEYWORD_ID=4103
37. IEA (2020) Defining energy access: 2020 methodology. Retrieved 10 Mar 2024, from International Energy Agency: <https://www.iea.org/articles/defining-energy-access-2020-methodology>
38. IEA (n.d.) Energy security. Retrieved 11 Mar 2024, from International Energy Agency: <https://www.iea.org/topics/energy-security>
39. IEEE (1990) IEEE standard computer dictionary: a compilation of IEEE standard computer glossaries. Institute of Electrical and Electronics Engineers, New York, NY
40. Jenn A, Springel K, Gopal AR (2018) Effectiveness of electric vehicle incentives in the United States. Energy Policy 119:359–356. <https://doi.org/10.1016/j.enpol.2018.04.065> [Crossref]
41. Ju N, Kim SH (2022) Electric vehicle resistance from Korean and American millennials: Environmental concerns and perception. Transp Res Part D Transp Environ 109. <https://doi.org/10.1016/j.trd.2022.103387>
42. Khastar M, Aslani A, Nejati M (2020) How does carbon tax affect social welfare and emission reduction in Finland? Energy Rep 6:736–744. <https://doi.org/10.1016/j.egyr.2020.03.001> [Crossref]
43. Kizilors C, Aydin D (2020) Effect of thermostat position and its set-point temperature on the performance of a domestic electric water heater. Int J Low-Carbon Technol 15(3):373–381. <https://doi.org/10.1093/ijlct/ctaa007>
44. KPMG (2023) KPMG's 2023 auto poll: the road ahead. KPMG Canada. Retrieved from <https://kpmg.com/ca/en/home/insights/2023/02/kpmg-2023-auto-poll.html>
45. Kuehl DT (1995) Airpower vs. electricity: electric power as a target for strategic air operations. In: Gooch J(ed) Airpower theory and practice. Taylor & Francis Group. <https://doi.org/10.4324/9781315036311>
46. Latorre-Biel J-I, Jiménez E, García JL, Martínez E, Jiménez E, Blanco J (2018) Replacement of electric resistive space heating by an air-source heat pump in a residential application. Environ Amortization Build Environ 141:193–205. <https://doi.org/10.1016/j.buildenv.2018.05.060> [Crossref]

47. Lee C-L, Jou C-JG (2013) Improving furnace energy efficiency through adjustment of damper angle. *Int J Hydrogen Energy* 38(5):2504–2509
48. Lowinger TC (1990) Japan's nuclear energy development policies: an overview. *J Energy Dev* 15(2):211–230. Retrieved from <https://www.jstor.org/stable/24807916>
49. Łukowicz H, Bartela Ł, Gładysz P, Qvist S (2023) Repowering a coal power plant steam cycle using modular light-water reactor technology. *Energies* 16(7). <https://doi.org/10.3390/en16073083>
50. Madden N, Lewis A, Davis M (2013) Thermal effluent from the power sector: an analysis of once-through cooling system impacts on surface water temperature. *Environ Res Lett* 8(3). <https://doi.org/10.1088/1748-9326/8/3/035006>
51. Magilligan FJ, Sneddon CS, Fox CA (2017) The social, historical, and institutional contingencies of dam removal. *Environ Manage* 59:982–994. <https://doi.org/10.1007/s00267-017-0835-2>
52. McCauley D, Jenkins K, Forman A (eds) (2018) Exploring the energy justice nexus. *Energy Policy*. Retrieved 12 Mar 2024, from <https://www.sciencedirect.com/journal/energy-policy/special-issue/10F8DMZXR9J>
53. Meadows D (1993) *Thinking in systems: a primer*. Chelsea Green Publishing, White River Junction, Vermont
54. Melendez M, Moriarty K, Dafoe W, Noblet S (2009) Status and issues for ethanol (E85) in the United States. U.S. Department of Energy—Energy Efficiency and Renewable Energy. Retrieved from <https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=48f3b3d591af15fb4f1542c0411047d5e77ac59f>
55. Nadel S (2018) Examples of energy savings, consumer economics, and greenhouse gas emissions reductions from replacing oil and propane furnaces, boilers, and water heaters with air-source heat pumps. American Council for an Energy-Efficient Economy, Washington, DC. Retrieved from <https://www.aceee.org/sites/default/files/publications/researchreports/a1803.pdf>
56. Nerlinger M, Utz S (2022) The impact of the Russia-Ukraine conflict on energy firms: a capital market perspective. *Fin Res Lett* 50. <https://www.sciencedirect.com/journal/finance-research-letters>, <https://doi.org/10.1016/j.frl.2022.103243>
57. Notteboom T, Haralambides H, Cullinane K (2024) The red sea crisis: ramifications for vessel operations, shipping networks, and maritime

supply chains. *Maritime Econ Logist* 26:1–26. <https://doi.org/10.1057/s41278-024-00287-z>
[Crossref]

58. Oke SA (2004) Alternative designs for petroleum product storage tanks for groundwater protection. *J Toxicol Environ Health A* 67:1717–1726. <https://doi.org/10.1080/15287390490492304>
[Crossref]
59. Ossai IC, Ahmed A, Hassan A, Hamid FS (2020) Remediation of soil and water contaminated with petroleum hydrocarbon: a review. *Environ Technol Innov* 17:100526. <https://doi.org/10.1016/j.eti.2019.100526>
[Crossref]
60. Palacín MR (2018) Understanding ageing in Li-ion batteries: a chemical issue. *Chem Soc Rev* 47:4924–4933. <https://doi.org/10.1039/C7CS00889A>
[Crossref]
61. Perdue M, Gottschalg R (2015) Energy yields of small grid connected photovoltaic system: effects of component reliability and maintenance. In: IET: 10th Photovoltaic science, application and technology conference (PVSAT-10). <https://doi.org/10.1049/iet-rpg.2014.0389>
62. Peruzzi L, Salata F, de Lieto Vollaro A, de Lieto Vollaro R (2014) The reliability of technological systems with high energy efficiency in residential buildings. *Energy Build* 68(Part A):19–24. <https://doi.org/10.1016/j.enbuild.2013.09.027>
63. QI (2020) Events, my dear boy, events. Retrieved from Quote Investigator: <https://quoteinvestigator.com/2020/08/31/events/>
64. Quadrelli R, Gómez DR, Watterson JD (n.d.) Stationary combustion. In: 2006 IPCC guidelines for national greenhouse gas inventories (vol 2: Energy). IPCC
65. Rathnayak M, Julnipitawong P, Tangtermsirikul S, Toochinda P (2018) Utilization of coal fly ash and bottom ash as solid sorbents for sulfur dioxide reduction from coal fired power plant: Life cycle assessment and applications. *J Clean Prod* 202:934–945. <https://doi.org/10.1016/j.jclepro.2018.08.204>
[Crossref]
66. Rautela R, Yadav BR, Kumar S (2023) A review on technologies for recovery of metals from waste lithium-ion batteries. *J Power Sourc* 580. <https://doi.org/10.1016/j.jpowsour.2023.233428>
67. Romero CA, Correa P, Echeverri EA, Vergara D (2024) Strategies for reducing automobile fuel consumption. *Appl Sci* 14(2). <https://doi.org/10.3390/app14020910>

68. Rosner K (2016) Water and electric power in Iraq and Syria: conflict and fragility implications for the future. Robert Strauss Center, Austin, Texas. Retrieved from https://strausscenter.org/wp-content/uploads/Water_and_Electric_Power_in_Iraq_and_Syria.pdf
69. Saleem A, Mushtaq A, Raza M, Ahmed R, Uddin AZ (2023) Enhance the corrosion resistance of underground petroleum tanks with the use of fiberglass-reinforced composite. Iran J Chem Chem Eng 42(8):2529–2537. Retrieved 26 Mar 2024, from https://www.ijcce.ac.ir/article_704495_69c7daf48d8bf97fe0809e0972987c02.pdf
70. Sareen S, Thomson H, Herrero ST, Gouveia JP, Lippert I, Lis A (2020) European energy poverty metrics: Scales, prospects and limits. Glob Transit 2:26–36. <https://doi.org/10.1016/j.glt.2020.01.003> [Crossref]
71. Scott A, MacIssac J (2024) Final report: modernizing energy from transition to transformation. Nova Scotia Clean Electricity Solutions Task Force, Halifax, Nova Scotia. Retrieved 24 Feb 2024, from <https://cetaskforce.ca/wp-content/uploads/2024/02/Report-February-23-2024-Final-Signed.pdf>
72. Sharma A, Shiwang J, Lee A, Peng W (2023) Equity implications of electric vehicles: a systematic review on the spatial distribution of emissions, air pollution and health impacts. Environ Res Lett 18:18–25. <https://doi.org/10.1088/1748-9326/acc87c> [Crossref]
73. Sheridan A (2020) The history of the kerosene lamp. Retrieved 30 Mar 2024, from Iowa State University—University Museums: <https://www.museums.iastate.edu/virtual/blog/2020/04/24/the-history-of-the-kerosene-lamp>
74. Shi X, Pan J, Wang H, Cai H (2019) Battery electric vehicles: what is the minimum range required? Energy 166:352–358. <https://doi.org/10.1016/j.energy.2018.10.056> [Crossref]
75. Smrekar J, Oman J, Širok B (2006) Improving the efficiency of natural draft cooling towers. Energy Convers Manage 47(9–10):1086–1100. <https://doi.org/10.1016/j.enconman.2005.07.012>
76. Stefanelli RD, Walker C, Kornelsen D, Lewis D, Martin DH, Masuda J, Richmond CA, Root E, Tait Neufeld H, Castleden H (2018) Renewable energy and energy autonomy: how Indigenous peoples in Canada are shaping an energy future. Environ Rev 27(1)

77. Sun C, Zhan Y, Du G (2020) Can value-added tax incentives of new energy industry increase firm's profitability? Evidence from financial data of China's listed companies. *Energy Econ* 86. <https://doi.org/10.1016/j.eneco.2019.104654>
78. Sunardi C, Hikmat YP, Margana AS, Sumeru K, Sukri MF (2020) Effect of room temperature set points on energy consumption in a residential air conditioning. In: *THERMOFLUID X: 10th international conference on thermofluids 2019*, vol 2248. AIP Conference Proceedings, Yogyakarta, Indonesia. <https://doi.org/10.1063/5.0018806>
79. Teixeira J (2019) IEEE 1366—reliability indices. Retrieved 18 Feb 2023, from National Grid: <https://site.ieee.org/boston-pes/files/2019/03/IEEE-1366-Reliability-Indices-2-2019.pdf>
80. TFD (2014b) Resilience. Retrieved 14 Aug 2014, from The Free Dictionary: <http://www.thefreedictionary.com/resilience>
81. Tkach D, Tkach D (2023) The main losses of the Ukrainian energy system as a result of massive attacks by Russia. *Econ Fin Manage Rev* 2. <https://doi.org/10.36690/2674-5208-2023-2-51-59>
82. Tran M-K, Bhatti A (2012) A review of range extenders in battery electric vehicles: current progress and future perspectives. *World Electr Veh J* 12(2). <https://doi.org/10.3390/wevj12020054>
83. UNEP (n.d.) Goal 7: affordable and clean energy. Retrieved March 10, 2024, from United Nations Environment Program: <https://www.unep.org/explore-topics/sustainable-development-goals/why-do-sustainable-development-goals-matter/goal-7>
84. van Bergeijk PA (2022) Sanctions against the Russian war on Ukraine: lessons from history and current prospects. *J World Trade* 56(4):571–586. <https://doi.org/10.54648/trad2022023> [Crossref]
85. van de Graaf T (2013) The “Oil Weapon” reversed? Sanctions against Iran and U.S.-EU structural power. In: *Middle East policy*, pp 145–163. Retrieved from <https://thijsvandegraaf.be/wp-content/uploads/2012/04/Van-de-Graaf-2013-Iran.pdf>
86. Velasco-Herrejón P, Bauwens T, Friant MC (2022) Challenging dominant sustainability worldviews on the energy transition: Lessons from Indigenous communities in Mexico and a plea for pluriversal technologies. *World Dev* 150. <https://doi.org/10.1016/j.worlddev.2021.105725>
87. Verma S, Mishra S, Gaur A, Chowdhury S, Mohapatra S, Dwivedi G, Verma P (2021) A comprehensive review on energy storage in hybrid

- electric vehicle. *J Traffic Transp Eng (English Edition)* 8(5):621–637. <https://doi.org/10.1016/j.jtte.2021.09.001>
88. Veza I, Asy'ari MZ, Idris M, Epin V, Fattah IR, Spraggon M (2023) Electric vehicle (EV) and driving towards sustainability: comparison between EV, HEV, PHEV, and ICE vehicles to achieve net zero emissions by 2050 from EV. *Alex Eng J* 82:459–467. <https://doi.org/10.1016/j.aej.2023.10.020> [Crossref]
89. Wang K-H, Pearn W-L (2003) Cost benefit analysis of series systems with warm standby components. *Math Methods Oper Res* 58(2):247–258. <https://doi.org/10.1007/s001860300274>
90. Wanyan Q, Ding G, Zhao Y, Li K, Deng J, Zheng Y (2018) Key technologies for salt-cavern underground gas storage construction and evaluation and their application. *Natural Gas Ind B* 5(6):623–630. <https://doi.org/10.1016/j.ngib.2018.11.01>
91. Webber P, Gouldson A, Kerr N (2015) The impacts of household retrofit and domestic energy efficiency schemes: a large scale, ex post evaluation. *Energy Policy* 84:35–43. <https://doi.org/10.1016/j.enpol.2015.04.020> [Crossref]
92. WHO (2024) WHO global air quality guidelines. World Health Organization. Retrieved from World Health Organization: <https://iris.who.int/bitstream/handle/10665/345329/9789240034228-eng.pdf?sequence=1&isAllowed=y>
93. WHO (n.d.) National air quality standards. Retrieved from World Health Organization—Swiss Tropical and Public Health Institute: <https://worldhealthorg.shinyapps.io/AirQualityStandards/>
94. Wieland R, Treseder R (1954) Internal corrosion in domestic fuel oil tank. *Corrosion*, pp 401–406. <https://doi.org/10.5006/0010-9312-10.11.401>
95. Xiang D, Lawley C (2019) The impact of British Columbia's carbon tax on residential natural gas consumption. *Energy Econ* 809:206–218. <https://doi.org/10.1016/j.eneco.2018.12.004> [Crossref]
96. Xie W, Min H, Zhi Y, Wang S, Yang Z, Xu X, Xiao F (2023) An inter-provincial continuous trading method based on energy block transaction in take or pay mode. In: 2023 6th International conference on energy, electrical and power engineering (CEEPE). IEEE, pp 1389–1394. <https://doi.org/10.1109/CEEPE58418.2023.10166825>
97. Xu C, Zhang Q, Yang Z, Li X, Xu G, Yang Y (2018) An improved supercritical coal-fired power generation system incorporating a

- supplementary supercritical CO₂ cycle. Appl Energy, pp 1319–1329.
<https://doi.org/10.1016/j.apenergy.2018.09.122>
98. Yourdon E (n.d.) Structured analysis wiki. Retrieved 5 Mar 2011, from
http://yourdon.com/strucanalysis/wiki/index.php?title=Table_of_Contents
 99. Zhang J, Meerman H, Benders R, Faaij A (2020) Comprehensive review of current natural gas liquefaction processes on technical and economic performance. Appl Therm Eng 166:114736. <https://doi.org/10.1016/j.applthermaleng.2019.114736> [Crossref]
 100. Zhao Y, Xu X, Qadrdan M, Wu J (2021) Optimal operation of compressor units in gas networks to provide flexibility to power systems. Appl Energy 290. <https://doi.org/10.1016/j.apenergy.2021.116740>
 101. Ziady H (2023) Why Big Oil isn't losing any sleep over the new climate deal. Retrieved from CNN: <https://www.cnn.com/2023/12/13/business/fossil-fuels-big-oil-cop28/index.html>
 102. Zou T, Khaloei M, MacKenzie D (2020) Effects of charging infrastructure characteristics on electric vehicle preferences of new and used car buyers in the United States. Transp Res Rec J Transp Res Board 2674(12). <https://doi.org/10.1177/036119812095>
-

Footnotes

1 These indicators can be used for both processes and entities (energy providers, sectors, and end-user services); for brevity, we will only refer to processes, drawing a distinction when necessary.

2 Crude oil, which is extracted, is a primary energy source with a price. Solar energy, another primary energy source, is considered “free”. The water used for the production of hydroelectricity is often associated with a fee or rent [6].

3 Randomly occurring events can be described by the exponential distribution shown in the following equation [21]:

$$R(t) = e^{-kt} = e^{\frac{-t}{MTBF}}$$

Reliability of a process at time t (k is λ or $\frac{1}{MTBF}$).

At time t equal to MTBE, the reliability becomes e^{-1} or about 37%; for an process, this can mean the probability of it operating without failure for as long as the MTBE is about 37%.

External Resilience Assessment of Energy Critical Infrastructures

Martin Hromada¹ , David Rehak² ,
Miltiadis Kontogeorgos³  and Neil Walker⁴ 

(1) Faculty of Applied Informatics, Tomas Bata University in Zlin, Zlin, Czech Republic

(2) Faculty of Safety Engineering, VSB—Technical University of Ostrava, Ostrava, Czech Republic

(3) Rina Consulting S.P.A., Rozzano, Italy

(4) International Association of Critical Infrastructure Protection Professionals, Hoddesdon, UK

 **Martin Hromada (Corresponding author)**
Email: hromada@utb.cz

 **David Rehak**
Email: david.rehak@vsb.cz

 **Miltiadis Kontogeorgos**
Email: miltiadis.kontogeorgos@rina.org

 **Neil Walker**
Email: neilw@torchmarketing.co.uk

Abstract

Energy Critical Infrastructures represent the most important sector of the Critical Infrastructure system. Not only the population depends on their service and supply continuity, but also all the sectors of Critical Infrastructures considered necessary for the functioning of society. Due to this reason, it is important that the Energy Critical Infrastructures achieve a high level of resilience capacity towards all types of hazards. This resilience can be perceived in the context of the environment either as internal or external. While the internal resilience of Energy Critical Infrastructures is ensured by critical entities (i.e. infrastructure owners/operators), external resilience is shaped by the external environment in which these infrastructures are located. The assessment of external resilience is currently still receiving insufficient attention though. Addressing this gap, the subject of this chapter is the presentation of the created approach on the assessment of the external resilience of Energy Critical Infrastructures in the context of the territorial unit disaster preparedness. It is also possible to consider the formulation of the aspect of external resilience as beneficial, which complements the existing framework of approaches to the implementation of internal resilience. The chapter is divided into three main parts, mainly investigating the importance and status of external resilience, the basic principles of external resilience assessment methodology, and the process for Energy Critical Infrastructures' external resilience assessment. At the end of the chapter, a case study of territorial unit disaster preparedness assessment with relation to the external resilience of the Energy Critical Infrastructures external resilience is presented.

Keywords Energy critical infrastructure – External resilience assessment – Disaster preparedness – Territorial unit – Case study

Abbreviations

CI Critical infrastructure

CIS Critical infrastructure specialist

CIERA Critical infrastructure elements resilience assessment

ECI Energy critical infrastructures

EU European Union

GDP Gross domestic product

SC Security council

TU Territorial unit

TSO Transmission system operator

1 Introduction

Critical Infrastructure (CI) was considered for long a system of technical and socio-economic infrastructures necessary for the provision of essential services [1]. These services are necessary for maintaining the most important of social functions, economic activities, public health, safety, and the environment. For this reason, it is essential that CIs are sufficiently resilient to the effects of internal and external threats [2]. In this context, the resilience of CI can be classified into internal and external. While internal resilience is understood as *“the ability of the critical infrastructure to reduce the magnitude and/or duration of disruptive events, i.e. incidents or disasters”* [3], external resilience of CI is perceived as *“territorial resilience which makes it possible to anticipate and manage possible risks of disasters arising either from the consequences of climate change, pandemics and health emergencies, or from social and political conflicts”* [4, 5]. Approaches to assessing internal resilience have been already introduced in a number of important publications [6–11], but the

assessment of external resilience in the context of disaster preparedness of Territorial Unit (TU) has not yet been comprehensively addressed.

Disaster preparedness of TU is considered a main pillar of ensuring the continuity of strategic functions of the territory. Given the current state of the security environment or the current trends in the occurrence of security threats, it is noticed an increase of pressure on the competent authorities of state administration and local self-government in the area of creating or optimizing the crisis management system or disaster preparedness process. The crucial role of disaster preparedness in the Czech Republic is strengthened by the relevant legal regulations, which, however, only form the framework of the issue. Therefore, the next followed step should be the development of relevant approaches, which on the one hand will allow to assess the disaster preparedness of the territory and on the other hand standardize disaster preparedness measures. The importance of disaster preparedness and its role are confirmed by the whole spectrum of authors. Carmeli and Schaubroeck [12] deal with the relationship and phenomenon learning from failures as a facilitator of disaster preparedness. In the [13] aspects are explored for increasing the motivation to build a complementary system of disaster preparedness from the perspective of municipal representatives. Theoretical discussion on the importance role of preparedness in the crisis management process were presented in [14, 15] and also from a practical point of view [16, 17].

The outputs of the above-mentioned publications is highlighting the importance of the disaster preparedness of the TU for emergencies, in the context of the CI elements that are located in territory and provide strategic functions and services. In the next chapter, therefore, the relationship between CI and the guaranteeing of the functional continuity for the TU will be investigated.

2 The Importance and Status of Energy Critical Infrastructures

Energy is the most important sector of CI. Not only the population depends on its supply, but also all dependent sectors of CI which are considered necessary for the society functions [18]. Due to this reason, the energy sector is rightly called uniquely critical [19], which means that a high level of resilience of all its elements must be permanently ensured. Failure of energy supplies would result in disruption of social functions, economic activities, public health, or state security [1].

2.1 The Position and Importance of Energy Critical Infrastructures in the Context of Ensuring the Functional Continuity of Territorial Unit

The provision of Energy Critical Infrastructures (ECI) functions is often perceived from the state functions perspective. However, this view has identified shortcomings in the context of selected security threats, which is described in [20, 21]. The most significant shortcoming is the fact that in the event of ECI element function failure or disruption, the disruption is often insignificant from the ensuring the basic functions of the state, while the element failure can have a major impact on vital functions of the TU. This fact is confirmed by [22–24]. This fact expresses to some extent the motivation to put into context the disaster preparedness of the TU with the ECI functionality, in a figurative sense to its external resilience [25].

The following text will therefore form a theoretical basis for the concept and issues of ECI external resilience in an obvious connection to the disaster preparedness of TU in a broader context.

2.2 Internal and External Resilience of Energy Critical Infrastructures

Based on the above, it is therefore reasonable that the level and quality of the disaster preparedness system of the TU is associated with ensuring the ECI function and thus from its external resilience perspective. The concept of CI external resilience has been presented in previous research attempts [26], where is perceived from the perspective of four dimensions—technical, organizational, economic, and social resilience. In this context, the article discusses about attributes as “*External crisis response equipment, First responder preparation, Government preparation, Trusted network community, Crisis regulation and legislation, Public crisis response budget a Societal situation awareness*”. Same authors [27, 28] preceded the understanding, while other authors are also describing the concept of external resilience [29, 30]. In these publications, there was a comparative analysis of the limitations of infrastructure resilience tools. Based on the above, it can be stated that the resilience of ECI is conceived by both external and internal resilience (Fig. 1).

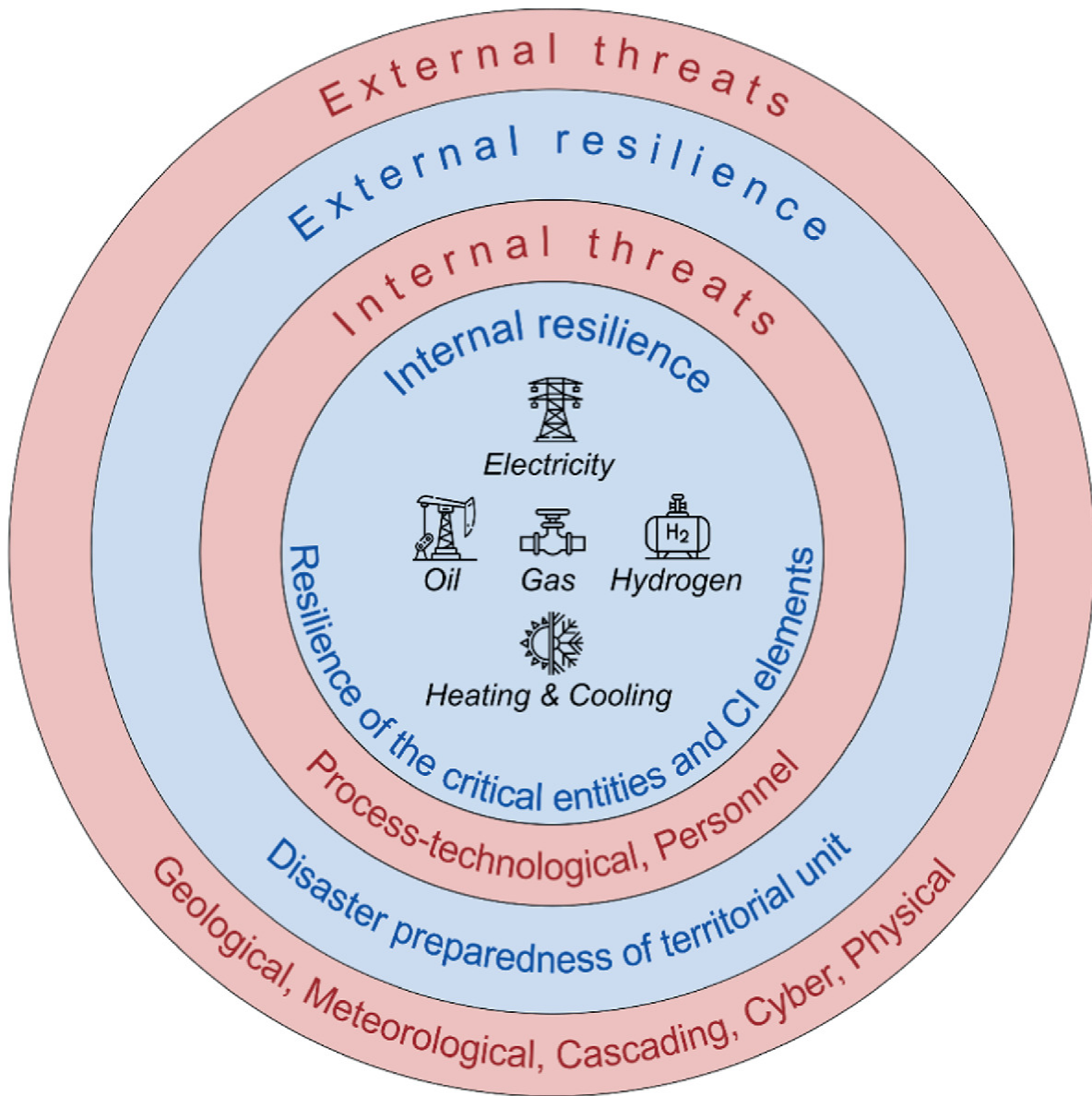


Fig. 1 Perceiving the resilience in the Energy Critical Infrastructures

The goal of internal resilience is the protection of ECI (i.e. critical subjects and CI elements operated by them) against internal and external threats. In contrast, the essence of the external resilience of ECI is the protection of the territory in which these infrastructures are located. By ensuring the disaster preparedness of TU, it is observed an increase in the resilience of not only the respective unit, but also the CI located in this territory.

Given the analysis of the current situation and the current needs to enhance disaster preparedness by

increasing external resilience, a methodology for the TU Disaster Preparedness Assessment with Relation to the External Resilience of the ECI was developed. In the following text, the methodology will be described in detail and at the end of this chapter also applied to the selected TU as a use case.

2.3 Disaster Preparedness in the Context of External Resilience

The combination of disaster preparedness and external resilience has not been a new phenomenon. For example [31] presented it applied within a strategic framework for assessing organizational and network resilience of 75 CI operators in the Greater Montreal area. Unlike the presented methodological procedure, the article is linked to the functions of CI and not to the functions of TU. Another article discussing the paradox of social resilience by questioning how cognitive strategies and coping mechanisms attenuate and accentuate resilience of the author team [32], which, however, relates disaster preparedness and external resilience to social resilience. The article *Organizational Resilience and Emergency Management of the Authors* [33] reflects the need that emergency services organizations need to address their own resilience issues in order to properly fulfil their community protection responsibilities. It is clear from this that this is not a concept with a link to the territorial unit as a whole, but to the authorities responsible for resolving disasters. In other works such as *Resilience is not a silver bullet—Harnessing resilience as core values and resource contexts in a double adaptive process* [34], *Resilience Learning for Emergency Plan Management in Organizations* [35], *Urban resilience for building a sustainable and safe environment* [36], *Value of Information on Resilience Decision-Making in Repeated*

Disaster Environments [37] or Transforming resilience in the context of a pandemic: results from a cross-industry case study exploring supply chain viability [38], there are observed scientific works which are related only to selected attributes and areas of disaster preparedness and external resilience issues connection, without significant convergence to the context of the CI functionality and functionality of the TU. The contribution of the following text will therefore be the mentioned convergence with benefit to ensure the functions of the TU.

3 Basic Principles of External Resilience Assessment Methodology

Ensuring adequate preparedness for disasters is one of the basic responsibilities of all TU. One of the fundamental and very important factors which significantly influence this process is the position and importance of ECI elements. The main reason is that for these elements, a respective disruption of their function has a serious impact on the security, safety, society lives and health, the provision of the population's living needs and last but not least, on the economic stability and sustainable development of the territory. Therefore, it is necessary to include the ECI aspect in the process of TU preparedness for disasters (hereinafter referred to as "disaster preparedness").

The ability of ECI elements to withstand the negative effects of disasters is determined by internal and external resilience. The internal resilience of these elements is defined by their robustness, recoverability and adaptability [3]. While external resilience results from the level of preparedness and ability of these elements to deal with specific disasters in direct connection and cooperation with the territory crisis management system. For the purposes of evaluating the internal resilience of ECI elements, the

CIERA methodology was certified in 2018 [11], however, the issues of external resilience have not yet been addressed.

3.1 Aim of the Proposed Methodology

The aim of proposed methodology is to provide a simple and effective tool for assessing the current level of TU disaster preparedness in relation to ECI and its external resilience. This methodology is primarily aimed at strengthening the preparedness of territorial authorities which are responsible for the effective territorial disaster preparedness. For the purposes of this methodology, these bodies are considered the security councils of regions and municipalities with extended powers (hereinafter referred to as security councils or SC) and regional crisis staffs, crisis staffs of municipalities with extended powers and crisis management staffs of municipalities.

A new parameter that this methodology provides is the integration and convergence of the ECI elements external resilience influence into the decision-making processes context of above-mentioned bodies in preparation for disasters and subsequently in their resolving. The main benefit of this methodology thus lies in the overall TU and at the same time the external environment security level increase of these elements during the spread of negative cascading and synergistic effects and impacts of disasters. The outcome of such an assessment shall provide to the relevant administrative authorities and all relevant critical entities the necessary feedback on the current preparedness level and response capability.

3.2 Subject of Methodology

The subject of proposed methodology is to define the necessary criteria and to establish a procedure for assessing the disaster preparedness of a TU, with emphasis on the position of ECI elements located in this area. The

resulting state of assessed TU preparedness subsequently reflects the level of assessed external resilience of ECI elements. Consequently, this methodology presents a method for assessing the disaster preparedness of the TU by reflecting the importance and specifics of ECI in the preparation and resolution of disasters.

3.3 Basic Framework of Territorial Unit Disaster Preparedness

The assessment of TU disaster preparedness (i.e. a region or municipalities) is a continuous and very dynamic process, which is influenced by a number of parameters, such as the emergence and change in the nature of threats, the development of new technologies to ensure measures to protect the population, etc.

Consistent to the terms of this methodology, in the time of a preparation for disasters and their subsequent resolving, it is recommended to incorporate a new functional role in the form of a Critical Infrastructure Specialist (CIS) into the existing structures of security councils and crisis staffs of TU. The scope of this role is a thorough knowledge of CI elements in the relevant territory for which it is established. In particular, it is about the current level of critical entities for disaster preparedness with a link to the disaster preparedness of local governments, including requirements for the provision of predetermined products, works or services, without which the disaster cannot be overcome.

It should be established that crisis management has the character of a continuous cyclical structure. For this reason, it is necessary to assume that the threats and subsequent risks of a TU, including the manner and possibilities of their resolving, may change over time [39]. The disaster preparedness planning process itself can be divided into the following four stages:

- **Stage I: Identification of relevant threats and their degree**

The subject of this initiation stage is the identification of risks possible sources or specific threats that may cause a disaster in the given conditions of the TU. Subsequently, for each such threat, an assessment of the negative effects and their impacts on the territory is carried out with regard to the TU security, provision of population basic living needs, lives and health of persons, property or the environment.

- **Stage II: Assessment of external factors**

The subject of this stage is the assessment of all identified disasters that may occur in a given area within the context of all factors having a direct impact on the preparation and resolving of these situations. These are mainly external factors, such as considering the possibility of the emergence and spread of cascading or synergistic impacts, assistance provided by neighbouring regions/municipalities, etc.

- **Stage III: Preparation of resources, measures, and related documentation**

The subject of this stage is the establishment of the necessary cooperation of stakeholders within the TU preparedness for disasters and their resolving. Furthermore, setting up the necessary processes, processing related planning, management, and contractual documentation, providing an overview of available forces and resources, necessary supplies, and other resources to ensure effective management of identified disasters and thus strengthen the external resilience of ECI elements.

- **Stage IV: Human resources training**

The subject of this stage is the provision of professional training and education to strengthen and refine not only theoretical knowledge and skills, but also especially the practical skills of persons involved in disaster preparedness of the TU. This training, its focus, form and frequency is addressed individually, within the organizational affiliation of individual entities, or by mutual agreement of several entities. The training must reflect the needs arising from the planned measures to address the relevant disasters.

4 Process for Energy Critical Infrastructure External Resilience Assessment

Based on the conditions defined above, the Process for ECI External Resilience Assessment is presented in the following part of the chapter. The importance of this process is the decision-making process and procedure for assessing the TU disaster preparedness in relation to the ECI external resilience. The following parts of the text describe in detail assessing the TU preparedness level to resolving disasters, assessing the significance of ECI elements in TU, and assessing the energy critical entity preparedness level for disasters.

4.1 Decision-Making Process in Assessing the Territorial Unit Disaster Preparedness in Relation to the Energy Critical Infrastructure External Resilience

The assessment of the TU disaster preparedness in relation to the ECI external resilience represents a comprehensive process, which consists of three sub-processes. Each of these sub-process covers a specific and coherent area that is directly related to the assessment. Arrangement of

individual processes, resp. their order is fixed. This is because the outputs of the source sub-process are a necessary input to the downstream sub-process.

The procedure of assessing the TU disaster preparedness in relation to the ECI external resilience is based on the following decision algorithm (see Fig. 2). As part of the introductory step, the basic elements and tools of the TU's preparedness for disasters are assessed. If the TU does not have these elements, then the whole assessment process is completed and in this case this methodology is not applicable for the given TU. Otherwise, each of these elements and tools will be assessed according to Assessment Sheet 1.

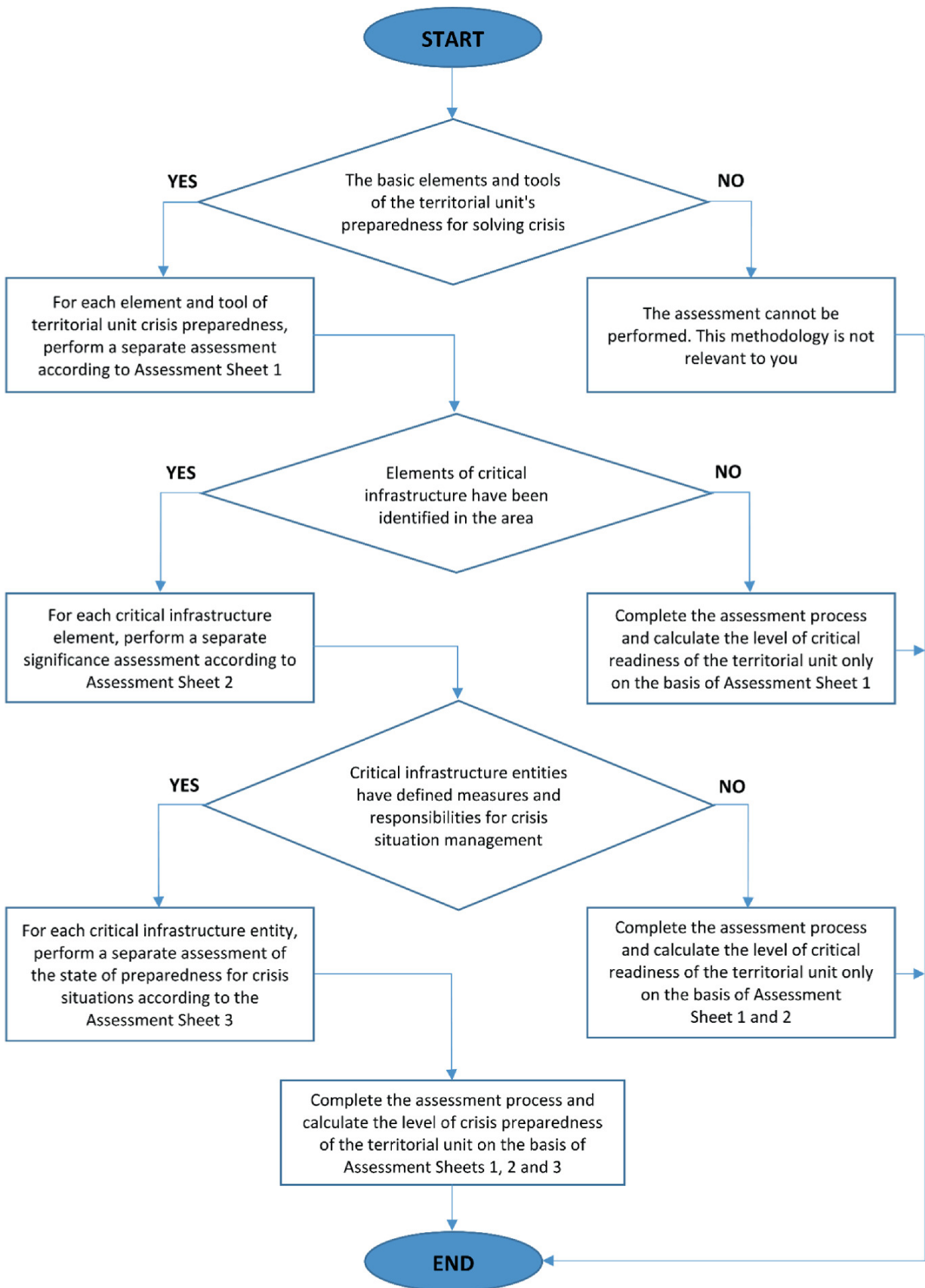


Fig. 2 The process of the territorial unit disaster preparedness assessing in relation to the Energy Critical Infrastructure external resilience

Then the assessment process should be proceeded to step two. It focuses on the fact whether ECI elements have been identified in a given area. If not, the assessment process ends and the final level will be assessed only based on the result of the previous step (i.e., step 1). The value of the occurrence of ECI elements and the ECI preparedness will be zero. However, if these elements have been identified in the given area, an assessment of their significance will be made according to Assessment Sheet 2. This assessment must be made for each element separately.

The subject of the third and simultaneously final step is to find out whether the individual energy critical entity have determined the necessary measures and responsibilities for resolving disasters. If not, the Assessment process is considered completed and the final level will be determined only based on the results of the previous steps (i.e., steps 1 and 2) respectively and the ECI preparedness value will be zero. In this case, the calculation formula remains the same. In the event that these measures and responsibilities are established by the entities, they will be assessed in accordance with the Assessment Sheet 3. This assessment must be made on a case-by-case basis. The final state of assessment then consists of the achieved results within all three steps or sub-processes, which is then interpreted in accordance with the reference scale according to Assessment Sheet 4.

4.2 The Procedure for Assessing the Territorial Unit Disaster Preparedness in Relation to the Energy Critical Infrastructure External Resilience

The procedure for assessing TU preparedness to deal with disasters in relation to the external resilience of the ECI

elements located in a given area consists of the following steps:

- Assessment of the territorial unit preparedness level to resolving disasters (UP).
- Assessment of the territorial unit Energy Critical Infrastructure elements significance (ES).
- Assessment of the energy critical entity preparedness level for disasters (EP).

The calculation of the TU disaster preparedness in relation to the ECI external resilience is perceived as an arithmetic average of the values of the above steps, according to the relation (1):

$$DP = \frac{1}{n} \sum_{i=1}^n D_i = \frac{UP + ES + EP}{3} \quad (1)$$

where DP = territorial unit disaster preparedness of the in relation to the energy critical infrastructure external resilience; D_i = i-th DP determinant; n = number of DP determinants; UP = territorial unit preparedness; ES = energy critical infrastructure elements significance; EP = energy critical entities preparedness.

Assessment Sheet 4 gives the assessment reference scale for the TU preparedness level in relation to the ECI external resilience. This part of the methodology also includes a proposal for measures to strengthen disaster preparedness level. All calculated values are rounded to two decimal places.

The responsibility for the assessment of the above steps is fully in the competence of the CI specialist, who will work closely with:

- Territorial authorities responsible for the preparation and resolution of disasters in the TU (i.e. the Security Council and the Crisis Staff),
- Individual energy critical entities located in the TU.

It is necessary to state, that the assessment of the TU preparedness level for resolving disasters, is fully within the competence and therefore within the responsibility of the Security Council Secretary, in cooperation with the relevant regional Fire and Rescue Service.

An example of practical application of this methodology is presented in the form of a case study in the last chapter of the article.

4.3 Assessing the Territorial Unit Preparedness Level to Resolving Disasters

The aim of this step is to assess the current TU preparedness level for resolving disasters. The main emphasis of the assessment is on the fulfilment of the obligations from the part of the competent authorities with the territorial jurisdiction and responsibility for the preparation and subsequent management of disasters (i.e. the Security Council and the Crisis Staff).

At the same time, the existence of other conditions necessary to ensure the preparedness of the TU to deal with disasters is assumed. However, all these conditions follow the proper preparation of the relevant territorial authorities, which are responsible for the overall concept and functionality of the entire crisis management system in the area.

The calculation of the TU preparedness level to resolving disasters is realized as a weighted average of individual variables defined below, according to the relation (2):

$$UP = \sum_{j=1}^m P_j v_j = TA \cdot w_{TA} + TTA \cdot w_{TTA} + CSW \cdot w_{CSW} + IN \cdot w_{IN} + FI \cdot w_{FI} \quad (2)$$

where UP = territorial unit preparedness; P_j = j th UP variable; w_j = the normalized weighting coefficient of the j th UP variable; m = number of variables UP; TA = territorial authorities responsible for preparing and dealing with disasters (number of positive answers/total number of questions); TTA = training of territorial authorities for preparing and dealing with disasters (number of positive answers/total number of questions); CSW = crisis staff workplace (number of positive answers/total number of questions); IN = information and disaster preparedness activities (number of positive answers/total number of questions); FI = financing (number of positive answers/total number of questions). Standardized weighting coefficients for calculating the TU preparedness level to resolving disasters are presented in Table 1.

Table 1 Standardized weighting coefficients for calculating the territorial unit preparedness level to resolving disasters

	TA	TTA	CSW	IN	FI	Σ
w_j	0.35	0.20	0.05	0.25	0.15	1.0

The determination of weight coefficients and their subsequent normalization was carried out on the basis of expert assessment of expected future method users (i.e. subjects of selected TU) using the Analytic Hierarchy Process method [40], which is based on a pairwise comparison of variants supporting the evaluation of criteria hierarchies.

For the needs of assessing the TU preparedness level to resolving disasters, a separate tool in the form of an Assessment Sheet 1 is specified.

4.4 Assessing the Significance of Energy Critical Infrastructure Elements in Territorial Unit

The aim of this step is to perform a detailed identification of all ECI elements significance related to the administrative territory of the assessed TU (so-called mapping of the ECI significance). The result of this mapping should not only be an unambiguous identification of these elements, but above all a determination of these elements impact level on society in the context of their functions disruption, identification of dependent CI sub-sectors and subsequent determination of endangerment of these elements. Each ECI element is assessed separately.

An integral part of this process is the determination of the following parameters:

- Name of the ECI element.
- Description of the ECI element, including sectoral classification;
- Identification of the energy critical entity;
- Determining the extent of the ECI element impacts to society when its functions are disrupted;
- Identification of dependent CI sub-sectors;
- Determining the threat to the ECI element function.

The calculation of the territorial unit Energy Critical Infrastructure elements significance is realized as a weighted average of the individual variables defined below, according to relations (3) and (4):

$$ES = \frac{1}{p} \sum_{x=1}^p ECIS_x \quad (3)$$

where ES = energy critical infrastructure elements significance [%]; $ECIS_x$ = assessment of the x-th energy critical infrastructure element significance [%]; p = number of territorial unit energy critical infrastructure elements.

$$\begin{aligned}
ECIS_x &= \sum_{k=1}^y 1 - ECIS_k w_k \\
&= 1 - (IL \cdot w_{IL} + DEP \cdot w_{DEP} + FT \cdot w_{FT})
\end{aligned} \tag{4}$$

where $ECIS_x$ = assessment of the x-th energy critical infrastructure element significance; $ECIS_k$ = k-th ECIS variable; w_k = normalized weighting coefficient of the k-th variable ECIS; y = number of ECIS variables; IL = the impact level on society in the event of the element disruption (number of deaths/250 or number of hospitalized for more than 24 h/2500 or financial loss/0.5% of GDP or number of persons affected by unavailability of necessary functions/125,000—maximum value of $IL = 1$); DEP = dependent critical infrastructure sub-sector (number of identified CI subsectors/total number of CI subsectors); FT = threats to the energy critical infrastructure element function (number of identified threats/total number of threats). Standardized weighting factors for the energy critical infrastructure elements assessment are presented in Table 2.

Table 2 Standardized weighting factors for the energy critical infrastructure elements assessment

	IL	DEP	FT	Σ
w_k	0.45	0.20	0.35	1.0

The determination of weight coefficients and their subsequent normalization was carried out using the same method as in the case of a TU preparedness assessment level to resolving disasters.

For the needs of identification and categorization of ECI, a separate tool in the form of an Assessment Sheet 2 is specified.

4.5 Assessing the Energy Critical Entity Preparedness Level for Disasters

The aim of this step is the assessment of the identified individual energy critical entities preparedness level to resolve disasters in the area of interest. The main emphasis in the assessment process is on ensuring the ECI elements protection in the form of established measures and responsibilities to resolving disasters.

The calculation of the energy critical entities preparedness level to resolving disasters is realized as a weighted average of individual variables defined below, according to relations (5) and (6):

$$EP = \frac{1}{q} \sum_{x=1}^q PCI_x \quad (5)$$

where EP = energy critical entities preparedness; PCI_x = assessment of the x-th energy critical entity preparedness; q = the number of energy critical entities in the assessed TU.

$$PCI_x = \sum_{k=1}^z PCIE_k w_k = RR \cdot w_{RR} + MR \cdot w_{MR} \quad (6)$$

where PCI_x = assessment of the x-th energy critical entity preparedness; $PCIE_k$ = k-th PCI variable; w_k = normalized weighting coefficient of the kth PCI; z = number of PCI variables; RR = responsibilities to resolving disasters (number of positive answers/total number of questions); MR = measures to resolving disasters (number of positive answers/total number of questions). Standardized weighting factors for the energy critical entities assessment are presented in Table 3.

Table 3 Standardized weighting factors for the energy critical entities assessment

	RR	MR	Σ
w_k	0.40	0.60	1.0

The determination of weight coefficients and their subsequent normalization was carried out using the same method as in the case of a TU preparedness assessment level to resolving disasters.

For assessing the energy critical entities preparedness level to resolving disasters, a separate tool in the form of an Assessment Sheet 3 is specified.

4.6 Assessment Sheets

The whole process for TU disaster preparedness assessment with relation to the ECI external resilience consists of three separates but directly related sub-processes. The first sub-process is an assessment of the TU preparedness level to resolving disasters. For the assessment of this sub-process is the fully responsible the Security Council Secretary of the given TU. The second sub-process is an assessment of the territorial unit ECI elements significance and the third is an assessment of the energy critical entity preparedness level for disasters. For both of these sub-processes, the responsible body for assessment process should be CI specialist. As part of its activities, it will prepare an analysis and assessment of ECI elements for the purpose of detailed identification and subsequent assessment of the external threat level to ECI elements in relation to disasters and at the same time the preparedness level of these elements.

Assessment of the TU preparedness level to resolving disasters (UP) is realized by filling in Assessment Sheet 1 and using mathematical relation (2). Within the assessment process, the status of fulfilment of individual variables (TA; TTA; CSW; IN; FI) will be assessed semi-quantitatively, where the verbal assessment will be assigned a numerical value (YES—1; NO—0).

The standardized weighting coefficients for calculating TU preparedness level to resolving disasters are set out in Assessment Sheet 1.

Assessment Sheet 1: Assessment of the Territorial Unit Preparedness Level for Resolving Disasters (UP)

Following Assessment Sheet 1 is designed to assessment of the TU preparedness level to resolving disasters.

ID	Assessed Area	Condition
1.	Territorial authorities responsible for preparing and dealing with disasters (TA)	
1.1	Is the Security Council constituted in the composition required by law?	
1.2	Is a crisis management staff established in the composition required by law?	
1.3	Has the permanent working group of crisis management staff position "Secretary of the Security Council"?	
1.4	Are members of the permanent working group of the crisis management staff "Employees of the territorial administrative office"?	
1.5	Are members of the permanent working group of the crisis management staff "Representatives of all basic components of Integrated Rescue System"?	
1.6	Are members of the permanent working group of the crisis management staff "Other experts with regard to resolved disasters"?	
1.7	Are the competencies and activities of the Security Council defined? (e.g. in the form of a statute or rules of procedures, etc.)	
1.8	Are competences and activities of Security Council defined (e.g. in the form of statute or rules of procedures, etc.)	
2.	Training of territorial authorities for preparing and dealing with disasters (TTA)	
2.1	Has the training of Security Council members been provided in the past 12 months?	
2.2	Has the training of Security Council members been ensured in the form of exercises in the past 12 months?	
2.3	Has the disaster been resolved in the past 12 months?	
3.	Crisis staff workplace (CSW)	
3.1	Is the place of the Security Council workplace determined?	
3.2	Do all members of the Security Council know where this workplace is located?	
3.3	Is there a backup workplace for Security Council?	
3.4	Do all members of the Security Council know where this backup workplace is located?	
3.5	Is the Security Council workplace (even the backup) equipped with the necessary technical and communication means?	
3.6	Is the Security Council (even backup) workplace secured against the entry of unauthorized persons?	
3.7	Is the Security Council (and backup) workplace secured against power failure in the range of at least 32 hours?	
3.8	Does the Security Council workplace (including the reserve) have sufficient facilities for all its members, in terms of rest, meals, drinking regime and hygiene needs?	
4.	Information and disaster preparedness activities (IN)	
4.1	Is an overview of possible sources of risks, including threat analysis, prepared and regularly updated?	
4.2	Is the crisis plan of the given territorial unit prepared and regularly updated?	
4.3	Is information on temporary changes in the residence of persons registered and shared with the regional fire brigade?	
4.4	Is information available on the capacities of medical, accommodation and catering facilities?	
4.5	Is information available on the amount, composition and location of hazardous substances produced, used or stored?	
4.6	Is information available on the amount of water retained in the reservoirs?	
4.7	Is information available on the layout of the interiors of production facilities, or other facilities important for resolving disasters, water supply, sewerage, product pipelines and energy networks?	
4.8	Is information available on buildings designed to protect the population in disasters, to provide rescue work, to store civil protection material and to protect and hide important operations?	
4.9	Is it evaluated after each disaster within the given territory?	
4.10	Is the possibility of acquainting a legal or natural person at their request with the nature of the potential threat, with the prepared crisis measures and with the method of their implementation?	
5.	Financing (FI)	
5.1	Is the amount of funds set aside within the budget for the relevant year to ensure preparation for the disaster?	
5.2	Is a special-purpose reserve of funds set aside within the budget for the relevant year to ensure preparation for the disaster and elimination of their consequences?	

Assessment of the territorial unit ECI elements significance is realized by filling in the Assessment Sheet 2 and using mathematical relations (3 and 4). First, all elements of ECI in the given TU will be identified. Subsequently, individual variable parameters are assessed for each element. This is to determine the impact level on society in the event of the element disruption (IL), identification of dependent CI sub-sectors (DEP) and determination of the threats to the ECI element function (FT).

The variable parameter IL can be expressed in the following ways:

- Estimated number of deaths/250.
- Estimated number of hospitalized for more than 24 h/2500.
- Financial loss estimate/0.5% of GDP.
- Estimated number of people affected by the unavailability of necessary functions/125,000.

As part of the assessment process, the evaluator chooses only one of the options (the most important from the territory perspective). The maximum value of the IL variable is 1, even if the calculation reaches larger values.

Binary logic and a semi-quantitative approach will be used in the assessment of the remaining variable factors (DEP; FT), where the verbal assessment will be assigned a numerical value (YES—1; NO—0). The final calculation of the given variables is given by a mathematical relation (4).

The standardized weighting coefficients for calculating the territorial unit ECI elements significance are set out in Assessment Sheet 2.

Assessment Sheet 2: Assessment of the x-th Territorial Unit Energy Critical Infrastructure Element Significance ($ECIS_x$)

This Assessment Sheet is intended for the detailed identification and subsequent categorization of ECI elements located in a given area.

Energy critical infrastructure element card (ID xxx)					
Identification part:					
Energy critical infrastructure element name:					
Description of the energy critical infrastructure element, including sectoral classification:					
Energy critical entity:					
The impact level on society in the event of the element disruption (IL):					
Estimated number of deaths [number of persons]					
Estimated number of hospitalized for more than 24 hours [number of persons]					
Financial loss estimate [% of GDP]					
Estimated number of people affected by the unavailability of necessary functions (or suffering another serious impact on everyday life causing a significant reduction) [number of people]					
Dependent critical infrastructure sub-sector¹ (DEP):					
Electricity		Rail transport		Cyber security area	
Natural gas		Air Transport		Financial market and currency	
Petroleum and petroleum products		Inland water transport		Integrated rescue system	
Water management		Technological elements of a fixed network of electronic communications		Radiation monitoring	
Crop production		Technological elements of the mobile network of electronic communications		Forecasting, warning and reporting service	
Animal production		Technological elements of networks for radio and television broadcasting		Public finance	
Food production		Technological elements for satellite communication		Social protection and employment	
Healthcare		Technological elements for postal services		Other state administration	
Road transport		Technological elements of information systems		Intelligence services	
Threats to the energy critical infrastructure element function² (FT):					
Prolonged drought				Epidemic	
Extreme high temperatures				Epiphytia	
Flash flood				Epizootic	
Heavy rainfall				A strange flood	
Extreme wind				Radiation accident	
Flood				Disruption of drinking water supply	
Disruption of food supply				Disruption of gas supplies	
Disruption of functionality of important electronic communications systems				Disruption of oil and oil product supplies	
Security breach of critical information infrastructure				Disruption of electricity supply	
Leakage of hazardous chemical during stationary equipment				Migration waves	
Disruption of the financial and foreign exchange economy				Violation of legality (including terrorism)	

¹If there are critical infrastructure elements in the area that are dependent on the assessed element, insert value one to the relevant sub-sectors (to which the dependent elements belong).

²Insert to the relevant hazard (i.e. hazard with unacceptable risk) value one.

Assessment of the energy critical entity preparedness level for disasters (EP) is realized by filling in the Assessment Sheet 3 and using mathematical relations (5 and 6). Within the assessment process, the status of fulfilment of individual variables (RR; MR) will be assessed semi-quantitatively, where the verbal assessment will be assigned a numerical value (YES—1; NO—0).

The standardized weighting coefficients for calculating the territorial unit ECI elements significance are set out in Assessment Sheet 3.

Assessment Sheet 3: Assessment of the Xth Energy Critical Entity Preparedness Level for Disasters (PCI_x)

This Assessment Sheet is intended for the energy critical entity preparedness level for disasters.

ID	Assessed Area	Condition
1.	Responsibilities to resolving disasters (RR)	
1.1	Is the organizational structure of the energy critical entity for disaster preparedness and resolution determined?	
1.2	Is a security liaison officer appointed?	
1.3	Are internal communication channels set up for crisis management?	
1.4	Are external communication channels set up for crisis management?	
1.5	Is the cooperation and conditions set for securing the necessary external resources for resolving the disaster (material and personnel)?	
2.	Measures to resolving disasters (MR)	
2.1	Are potential threats to the functionality of the energy critical infrastructure element identified?	
2.2	Are measures in place to protect the energy critical infrastructure element based on defined threats?	
2.3	Is the energy critical entity operator security plan (OSP) elaborated?	
2.4	Has the OSP been updated in the last 4 years?	
2.5	Has the OSP been continuously updated or at least checked for timeliness in the past year?	
2.6	Has the functionality of OSP been practically tested in the past 2 years in the form of exercises?	
2.7	Is the periodic acquaintance of the employees of the energy critical entity with the issue of preparation and solution of disasters?	

As already stated, process for TU disaster preparedness assessment with relation to the external resilience of ECI elements located in a given area consists of the following steps and mathematical relationships:

- Assessment of the TU preparedness level for resolving disasters (mathematical relation 2).
- Assessment of the territorial unit ECI elements significance (mathematical relations 3 and 4).
- Assessment of the energy critical entity preparedness level for disasters (mathematical relations 5 and 6).

The final assessment of the TU disaster preparedness in relation to the ECI external resilience is carried out by applying the established mathematical relationship (1) and categorizing the assessment results according to the Table 4.

Table 4 Reference scale for assessing the territorial unit disaster preparedness level

Category of territorial unit disaster preparedness	Territorial unit disaster preparedness level
Very good preparedness	0.76-1.00
Acceptable preparedness	0.51-0.75
Insufficient preparedness	≤ 0.50

Note The classification of territorial unit disaster preparedness level is philosophically based on the CIERA methodology [11]

This reference scale is designed to categorize the assessment results into three levels of TU disaster preparedness and the subsequent measures proposal to strengthen the disaster preparedness level.

If the disaster preparedness reaches the level of 0.76-1.00, it is considered as excellent level, which indicates that all the set measures are more than sufficient to manage and resolving disasters.

If the disaster preparedness reaches the level of 0.51-0.75, it is considered as sufficient level, which indicates that the existing measures are sufficient to manage and resolving disasters but provide room for improvements. In

this case, it is appropriate to pay particular attention to those variables for which the answer NO was given.

If the disaster preparedness reaches the level ≤ 0.50 , it is considered as insufficient level, which indicates that most of the existing measures are insufficient to manage and resolving disasters. In this case, it is necessary to review all variables and start the process of restoring the entire disaster preparedness system. Particular attention should be paid to:

- the establishment of territorial authorities responsible for the preparation and resolving of disasters,
 - training of territorial authorities responsible for the preparation and resolving of disasters,
 - information and activities to ensure disaster preparedness,
 - minimizing the impact on society in the event of disruption of the CI elements,
 - disasters resolving measures,
 - preparedness of energy critical entities for disasters.
-

5 Case Study of Energy Critical Infrastructures External Resilience Assessment

Case study of TU disaster preparedness assessment with relation to the ECI external resilience was carried out in cooperation with the Department of the Zlín Region Governor Office (Czech Republic), Crisis Management Officer. As part of the assessment process, the preparedness of the TU to resolving disasters was assessed in the first step (UP).

Assessment of the TU preparedness level to resolving disasters (UP) is realized by filling in Assessment Sheet 1 and using mathematical relation (2). Within the assessment

process, the status of fulfilment of individual variables (TA; TTA; CSW; IN; FI) will be assessed semi-quantitatively, where the verbal assessment will be assigned a numerical value (YES—1; NO—0).

ID	Assessed Area	Condition
1.	Territorial authorities responsible for preparing and dealing with disasters (TA)	
1.1	Is the Security Council constituted in the composition required by law?	1
1.2	Is a crisis management staff established in the composition required by law?	1
1.3	Has the permanent working group of crisis management staff position "Secretary of the Security Council"?	1
1.4	Are members of the permanent working group of the crisis management staff "Employees of the territorial administrative office"?	1
1.5	Are members of the permanent working group of the crisis management staff "Representatives of all basic components of Integrated Rescue System"?	1
1.6	Are members of the permanent working group of the crisis management staff "Other experts with regard to resolved disasters"?	1
1.7	Are the competencies and activities of the Security Council defined? (e.g. in the form of a statute or rules of procedures, etc.)	1
1.8	Are competences and activities of Security Council defined (e.g. in the form of statute or rules of procedures, etc.)	1
2.	Training of territorial authorities for preparing and dealing with disasters (TTA)	
2.1	Has the training of Security Council members been provided in the past 12 months?	1
2.2	Has the training of Security Council members been ensured in the form of exercises in the past 12 months?	0
2.3	Has the disaster been resolved in the past 12 months?	1
3.	Crisis staff workplace (CSW)	
3.1	Is the place of the Security Council workplace determined?	1
3.2	Do all members of the Security Council know where this workplace is located?	1
3.3	Is there a backup workplace for Security Council?	1
3.4	Do all members of the Security Council know where this backup workplace is located?	1
3.5	Is the Security Council workplace (even the backup) equipped with the necessary technical and communication means?	1
3.6	Is the Security Council (even backup) workplace secured against the entry of unauthorized persons?	1
3.7	Is the Security Council (and backup) workplace secured against power failure in the range of at least 32 hours?	1
3.8	Does the Security Council workplace (including the reserve) have sufficient facilities for all its members, in terms of rest, meals, drinking regime and hygiene needs?	1
4.	Information and disaster preparedness activities (IN)	
4.1	Is an overview of possible sources of risks, including threat analysis, prepared and regularly updated?	1
4.2	Is the crisis plan of the given territorial unit prepared and regularly updated?	1
4.3	Is information on temporary changes in the residence of persons registered and shared with the regional fire brigade?	1
4.4	Is information available on the capacities of medical, accommodation and catering facilities?	1
4.5	Is information available on the amount, composition and location of hazardous substances produced, used or stored?	1
4.6	Is information available on the amount of water retained in the reservoirs?	1
4.7	Is information available on the layout of the interiors of production facilities, or other facilities important for solving disasters, water supply, sewerage, product pipelines and energy networks?	1
4.8	Is information available on buildings designed to protect the population in disasters, to provide rescue work, to store civil protection material and to protect and hide important operations?	1
4.9	Is it evaluated after each disaster within the given territory?	1
4.10	Is the possibility of acquainting a legal or natural person at their request with the nature of the potential threat, with the prepared crisis measures and with the method of their implementation?	1
5.	Financing (FI)	
5.1	Is the amount of funds set aside within the budget for the relevant year to ensure preparation for the disaster?	1
5.2	Is a special-purpose reserve of funds set aside within the budget for the relevant year to ensure preparation for the disaster and elimination of their consequences?	1

Using the mathematical relation (7) and Table 1, TU preparedness level for resolving disasters (PU) was assessed:

$$\begin{aligned}
 UP &= \sum_{j=1}^m P_j v_j = TA \cdot w_{TA} + TTA \cdot w_{TTA} \\
 &\quad + CSW \cdot w_{CSW} + IN \cdot w_{IN} + FI \cdot w_{FI} \\
 UP &= 8/8 \cdot 0.35 + 2/3 \cdot 0.20 \\
 &\quad + 8/8 \cdot 0.05 + 10/10 \cdot 0.25 \\
 &\quad + 2/2 \cdot 0.15 \\
 UP &= 1 \cdot 0.35 + 0.67 \cdot 0.20 \\
 &\quad + 1 \cdot 0.05 + 1 \cdot 0.25 + 1 \cdot 0.15 \\
 PU &= 0.93
 \end{aligned} \tag{7}$$

In the next step of the methodology application, the territorial unit ECI elements significance (CI) was assessed, which is realized by filling in the Assessment Sheet 2 and using mathematical relations (3 and 4).

As part of this step, three (within the selected sector) elements of ECI in the given area were identified for better clarity. Subsequently, individual variable parameters were assessed for each element. These were the determination of the impact level on society in the event of the element disruption (IL), the determination of the CI dependent sub-sectors (DEP) and the determination of the threats to the ECI element function (FT).

As part of the evaluation process, the variable parameter “number of persons affected by unavailability of necessary functions/125,000” was selected.

Binary logic and a semi-quantitative approach will be used in the assessment of the remaining variable factors (DEP; FT), where the verbal assessment will be assigned a numerical value (YES—1; NO—0). The final calculation of the given variables is given by a mathematical relation (4).

The standardized weighting coefficients for calculating the territorial unit ECI elements significance are set out in Table [2](#).

Energy critical infrastructure element card (ID 001)					
Identification part:					
Energy critical infrastructure element name:	Power station				
Description of the energy critical infrastructure element, including sectoral classification:	Power station 400/110 kV,				
Energy critical entity:	TSO - Electricity				
The impact level on society in the event of the element disruption (IL):					
Estimated number of deaths [number of persons]					
Estimated number of hospitalized for more than 24 hours [number of persons]					
Financial loss estimate [% of GDP]					
Estimated number of people affected by the unavailability of necessary functions (or suffering another serious impact on everyday life causing a significant reduction) [number of people]					1
Dependent critical infrastructure sub-sector¹ (DEP):					
Electricity	1	Rail transport	1	Cyber security area	1
Natural gas	1	Air Transport	0	Financial market and currency	1
Petroleum and petroleum products	1	Inland water transport	0	Integrated rescue system	1
Water management	0	Technological elements of a fixed network of electronic communications	1	Radiation monitoring	0
Crop production	0	Technological elements of the mobile network of electronic communications	1	Forecasting, warning and reporting service	1
Animal production	0	Technological elements of networks for radio and television broadcasting	1	Public finance	1
Food production	1	Technological elements for satellite communication	1	Social protection and employment	0
Healthcare	1	Technological elements for postal services	1	Other state administration	0
Road transport	1	Technological elements of information systems	1	Intelligence services	0
Threats to the energy critical infrastructure element function² (FT):					
Prolonged drought	0	Epidemic	0		
Extreme high temperatures	0	Epiphytia	0		
Flash flood	1	Epizootic	0		
Heavy rainfall	1	A strange flood	0		
Extreme wind	1	Radiation accident	0		
Flood	0	Disruption of drinking water supply	0		
Disruption of food supply	0	Disruption of gas supplies	0		
Disruption of functionality of important electronic communications systems	1	Disruption of oil and oil product supplies	0		
Security breach of critical information infrastructure	1	Disruption of electricity supply	1		
Leakage of hazardous chemical during stationary equipment	0	Migration waves	0		
Disruption of the financial and foreign exchange economy	0	Violation of legality (including terrorism)	1		

¹If there are critical infrastructure elements in the area that are dependent on the assessed element, insert value one to the relevant sub-sectors (to which the dependent elements belong).

²Insert to the relevant hazard (i.e. hazard with unacceptable risk) value one.

Numerical value of the territorial unit ID 001 ECI element significance ($ECIS_1$):

$$\begin{aligned}
 ECIS_x &= \sum_{k=1}^y 1 - ECIS_k w_k \\
 &= 1 - (IL \cdot w_{IL} + DEP \cdot w_{DEP} + FT \cdot w_{FT}) \\
 ECIS_1 &= 1 - (IL_1 \cdot w_{IL} + DEP_1 \cdot w_{DEP} + FT_1 \cdot w_{OF}) \quad (8) \\
 ECIS_1 &= 1 - (1 \cdot 0.45 + 18/27 \cdot 0.20 + 7/22 \cdot 0.35) \\
 ECIS_1 &= 1 - (0.45 + 0.13 + 0.11) \\
 ECIS_1 &= 0.31
 \end{aligned}$$

Energy critical infrastructure element card (ID 002)					
Identification part:					
Energy critical infrastructure element name:	Transmission system line 417				
Description of the energy critical infrastructure element, including sectoral classification:	Transmission system line 417,				
Energy critical entity:	TSO - Electricity				
The impact level on society in the event of the element disruption (IL):					
Estimated number of deaths [number of persons]					
Estimated number of hospitalized for more than 24 hours [number of persons]					
Financial loss estimate [% of GDP]					
Estimated number of people affected by the unavailability of necessary functions (or suffering another serious impact on everyday life causing a significant reduction) [number of people]					1
Dependent critical infrastructure sub-sector¹ (DEP):					
Electricity	1	Rail transport	1	Cyber security area	1
Natural gas	1	Air Transport	1	Financial market and currency	1
Petroleum and petroleum products	1	Inland water transport	0	Integrated rescue system	1
Water management	1	Technological elements of a fixed network of electronic communications	1	Radiation monitoring	0
Crop production	0	Technological elements of the mobile network of electronic communications	1	Forecasting, warning and reporting service	1
Animal production	1	Technological elements of networks for radio and television broadcasting	1	Public finance	1
Food production	1	Technological elements for satellite communication	1	Social protection and employment	0
Healthcare	1	Technological elements for postal services	1	Other state administration	0
Road transport	1	Technological elements of information systems	1	Intelligence services	0

Threats to the energy critical infrastructure element function ² (<i>FT</i>):			
Prolonged drought	0	Epidemic	0
Extreme high temperatures	0	Epiphytia	0
Flash flood	0	Epizootic	0
Heavy rainfall	0	A strange flood	0
Extreme wind	1	Radiation accident	0
Flood	0	Disruption of drinking water supply	0
Disruption of food supply	0	Disruption of gas supplies	0
Disruption of functionality of important electronic communications systems	1	Disruption of oil and oil product supplies	0
Security breach of critical information infrastructure	1	Disruption of electricity supply	1
Leakage of hazardous chemical during stationary equipment	0	Migration waves	0
Disruption of the financial and foreign exchange economy	0	Violation of legality (including terrorism)	1

¹If there are critical infrastructure elements in the area that are dependent on the assessed element, insert value one to the relevant sub-sectors (to which the dependent elements belong).

²Insert to the relevant hazard (i.e. hazard with unacceptable risk) value one.

Numerical value of the territorial unit ID 002 ECI element significance ($ECIS_1$):

$$\begin{aligned}
 ECIS_x &= \sum_{k=1}^y 1 - ECIS_k w_k \\
 &= 1 - (IL \cdot w_{IL} + DEP \cdot w_{DEP} + FT \cdot w_{FT}) \\
 ECIS_2 &= 1 - (IL_2 \cdot w_{IL} + DEP_2 \cdot w_{DEP} + FT_2 \cdot w_{OF}) \quad (9) \\
 ECIS_2 &= 1 - (1 \cdot 0.45 + 21/27 \cdot 0.20 + 5/22 \cdot 0.35) \\
 ECIS_2 &= 1 - (0.45 + 0.15 + 0.08) \\
 ECIS_2 &= 0.32
 \end{aligned}$$

Energy critical infrastructure element card (ID 003)					
Identification part					
Energy critical infrastructure element name:	National oil pipeline				
Description of the energy critical infrastructure element, including sectoral classification:	National oil pipeline with a nominal diameter of at least 200 mm,				
Energy critical entity:	TSO - Gas				
The impact level on society in the event of the element disruption (IL):					
Estimated number of deaths [number of persons]					
Estimated number of hospitalized for more than 24 hours [number of persons]					
Financial loss estimate [% of GDP]					
Estimated number of people affected by the unavailability of necessary functions (or suffering another serious impact on everyday life causing a significant reduction) [number of people]					1
Dependent critical infrastructure sub-sector¹ (DEP):					
Electricity	1	Rail transport	1	Cyber security area	0
Natural gas	0	Air Transport	0	Financial market and currency	0
Petroleum and petroleum products	1	Inland water transport	0	Integrated rescue system	1
Water management	0	Technological elements of a fixed network of electronic communications	0	Radiation monitoring	0
Crop production	0	Technological elements of the mobile network of electronic communications	0	Forecasting, warning and reporting service	0
Animal production	0	Technological elements of networks for radio and television broadcasting	0	Public finance	0
Food production	1	Technological elements for satellite communication	0	Social protection and employment	0
Healthcare	1	Technological elements for postal services	0	Other state administration	0
Road transport	1	Technological elements of information systems	0	Intelligence services	0
Threats to the energy critical infrastructure element function² (FT):					
Prolonged drought	0	Epidemic	0		
Extreme high temperatures	1	Epiphytia	0		
Flash flood	1	Epizootic	0		
Heavy rainfall	1	A strange flood	1		
Extreme wind	0	Radiation accident	0		
Flood	1	Disruption of drinking water supply	0		
Disruption of food supply	0	Disruption of gas supplies	0		
Disruption of functionality of important electronic communications systems	1	Disruption of oil and oil product supplies	1		
Security breach of critical information infrastructure	1	Disruption of electricity supply	1		
Leakage of hazardous chemical during stationary equipment	1	Migration waves	0		
Disruption of the financial and foreign exchange economy	0	Violation of legality (including terrorism)	1		

¹If there are critical infrastructure elements in the area that are dependent on the assessed element, insert value one to the relevant sub-sectors (to which the dependent elements belong).

²Insert to the relevant hazard (i.e. hazard with unacceptable risk) value one.

Numerical value of the territorial unit ID 003 ECI element significance ($ECIS_1$):

$$\begin{aligned}
 ECIS_x &= \sum_{k=1}^y 1 - ECIS_k w_k \\
 &= 1 - (IL \cdot w_{IL} + DEP \cdot w_{DEP} + FT \cdot w_{FT}) \\
 ECIS_3 &= 1 - (IL_3 \cdot w_{IL} + DEP_3 \cdot w_{DEP} + FT_3 \cdot w_{OF}) \quad (10) \\
 ECIS_3 &= 1 - (1 \cdot 0.45 + 7/27 \cdot 0.20 + 11/22 \cdot 0.35) \\
 ECIS_3 &= 1 - (0.45 + 0.05 + 0.18) \\
 ECIS_3 &= 0.32
 \end{aligned}$$

Calculation of territorial unit ECI elements significance (ES) (within the set restrictive conditions) was carried out as a weighted average of the partial values ID001-ID003 elements significance according to relation (11):

$$\begin{aligned}
 ES &= \frac{1}{p} \sum_{x=1}^p ECIS_x \\
 ES &= \frac{ECIS_1 + ECIS_2 + ECIS_3}{3} \quad (11) \\
 ES &= \frac{0.31 + 0.32 + 0.32}{3} \\
 ES &= 0.32
 \end{aligned}$$

Next step of methodology application is the assessment of the individual energy critical entities preparedness level to resolve identified disasters within the area of interest. The main emphasis in the assessment process is on ensuring the ECI elements protection in the form of established measures and responsibilities to resolving disasters.

Assessment of the energy critical entity preparedness level for disasters (EP) is realized by filling in the Assessment Sheet 3 and using mathematical relations (5 and 6). Within the assessment process, the status of

fulfilment of individual variables (RR; MR) will be assessed semi-quantitatively, where the verbal assessment will be assigned a numerical value (YES—1; NO—0).

The standardized weighting coefficients for calculating the territorial unit ECI elements significance are set out in Table 3.

$$PCI_x = \sum_{k=1}^z PCIE_k w_k = RR \cdot w_{RR} + MR \cdot w_{MR} \quad (12)$$

ID	Assessed Area	Condition
1.	Responsibilities to resolving disasters (RR)	
1.1	Is the organizational structure of the energy critical entity for disaster preparedness and resolution determined?	1
1.2	Is a security liaison officer appointed?	1
1.3	Are internal communication channels set up for crisis management?	1
1.4	Are external communication channels set up for crisis management?	1
1.5	Is the cooperation and conditions set for securing the necessary external resources for resolving the disaster (material and personnel)?	1
2.	Measures to resolving disasters (MR)	
2.1	Are potential threats to the functionality of the energy critical infrastructure element identified?	1
2.2	Are measures in place to protect the energy critical infrastructure element based on defined threats?	1
2.3	Is the energy critical entity operator security plan (OSP) elaborated?	1
2.4	Has the OSP been updated in the last 4 years?	1
2.5	Has the OSP been continuously updated or at least checked for timeliness in the past year?	1
2.6	Has the functionality of OSP been practically tested in the past 2 years in the form of exercises?	1
2.7	Is the periodic acquaintance of the employees of the energy critical entity with the issue of preparation and solution of disasters?	1

Numerical value of the energy critical entity preparedness level for disasters (TSO—Electricity) (PCI_1):

$$\begin{aligned}
 PCI_x &= \sum_{k=1}^z PCIE_k w_k \\
 &= RR \cdot w_{RR} + MR \cdot w_{MR} \\
 PCI_1 &= RR_1 \cdot w_{RR} + MR_1 \cdot w_{MR} \\
 PCI_1 &= 5/5 \cdot 0.40 + 7/7 \cdot 0.60 \\
 PCI_1 &= 1 \cdot 0.40 + 1 \cdot 0.60 \\
 PCI_1 &= 1
 \end{aligned} \quad (13)$$

ID	Assessed Area	Condition
1.	Responsibilities to resolving disasters (RR)	
1.1	Is the organizational structure of the energy critical entity for disaster preparedness and resolution determined?	1
1.2	Is a security liaison officer appointed?	1
1.3	Are internal communication channels set up for crisis management?	1
1.4	Are external communication channels set up for crisis management?	1
1.5	Is the cooperation and conditions set for securing the necessary external resources for resolving the disaster (material and personnel)?	1
2.	Measures to resolving disasters (MR)	
2.1	Are potential threats to the functionality of the energy critical infrastructure element identified?	1
2.2	Are measures in place to protect the energy critical infrastructure element based on defined threats?	1
2.3	Is the energy critical entity operator security plan (OSP) elaborated?	1
2.4	Has the OSP been updated in the last 4 years?	1
2.5	Has the OSP been continuously updated or at least checked for timeliness in the past year?	1
2.6	Has the functionality of OSP been practically tested in the past 2 years in the form of exercises?	0
2.7	Is the periodic acquaintance of the employees of the energy critical entity with the issue of preparation and solution of disasters?	1

Numerical value of the energy critical entity preparedness level for disasters (TSO—Gas) (PCI_2):

$$\begin{aligned}
 PCI_x &= \sum_{k=1}^z PCIE_k w_k = RR \cdot w_{RR} + MR \cdot w_{MR} \\
 PCI_2 &= RR_2 \cdot w_{RR} + MR_2 \cdot w_{MR} \\
 PCI_2 &= 5/5 \cdot 0.40 + 6/7 \cdot 0.60 \\
 PCI_2 &= 1 \cdot 0.40 + 0.86 \cdot 0.60 \\
 PCI_2 &= 0.92
 \end{aligned} \tag{14}$$

The calculation of the Zlin region energy critical entities preparedness level to resolving disasters is realized as a weighted average of individual variables defined below, according to relations (15):

$$\begin{aligned}
 EP &= \frac{1}{q} \sum_{x=1}^q PCI_x \\
 PS &= \frac{1 + 0.92}{2} \\
 PS &= 0.96
 \end{aligned} \tag{15}$$

The procedure for assessing TU preparedness to deal with disasters in relation to the external resilience of ECI

elements located in a given area consists of the following steps:

- Assessment of the territorial unit preparedness level to resolving disasters (UP).
- Assessment of the territorial unit ECI elements significance (CI).
- Assessment of the energy critical entity preparedness level for disasters (EP).

The calculation of the TU disaster preparedness in relation to the ECI external resilience is realized as an arithmetic average of the values of the above steps, according to the relation (16):

$$DP = \frac{1}{n} \sum_{i=1}^n D_i = \frac{UP + ES + EP}{3} \quad (16)$$

For assessment of TU disaster preparedness in relation to the external resilience the Table 4 was used.

Category of territorial unit disaster preparedness	Territorial unit disaster preparedness level
Very good preparedness	0.76-1.00
Acceptable preparedness	0.51-0.75
Insufficient preparedness	≤0.50

The calculation of the TU disaster preparedness in relation to the ECI external resilience is realized as an arithmetic average of the values of the above steps, according to the relation (17):

$$DP = \frac{1}{n} \sum_{i=1}^n D_i = \frac{UP + ES + EP}{3} \quad (17)$$

where:

$$UP = 0.93$$

$$ES = 0.32$$

$$EP = 0.96$$

Numerical value of TU disaster preparedness level in relation to the ECI external resilience (DP):

$$DP = \frac{0.93 + 0.32 + 0.96}{3}$$

$$DP = 0.73$$

Numerical value of TU disaster preparedness level in relation to the ECI external resilience ($DP = 0.73$) expresses the fact that the Zlín Region (with the set restrictive criteria) is in the category “Acceptable preparedness”.

6 Conclusion

This chapter analyses the importance and the role of disaster preparedness of TU in the context of the necessity to ensure functional continuity of the TU. Given the current state of knowledge and the current needs of the National Energy Resilience Program of the Czech Republic or the basis of the State Energy Conception of the Czech Republic, disaster preparedness is associated with the issues of protection and resilience of ECI in a broader context. The publication pointed out the need to perceive the position of ECI not only from the perspective of ensuring the state function but also of ensuring the TU functional continuity. This fact was materialized through the attribute of external resilience as the interface of the influence of ECI elements and TU functions.

The contribution of the article is the presentation of a comprehensive methodology for TU Disaster Preparedness Assessment with Relation to the ECI External Resilience, whose functionality has been tested in a selected TU (Zlín

Region) as a certain form of Use Case. The added value of the methodology is the development of a simple and effective tool for assessing the current level of TU disaster preparedness in relation to ECI and its external resilience. This methodology provide mechanism for the strengthening of the preparedness of territorial authorities responsible for preparing the TU for disasters. A new parameter that this methodology introduces is the integration of the influence of external resilience of ECI elements into the decision-making processes context of above-mentioned bodies in preparation for disasters and subsequently in their resolving.

The main beneficial outcome of this methodology thus lies in the increase of both the overall area's the external environment's security level at the same time, towards the spreading of post-disaster negative cascading and synergistic effects and impacts. The outcome of such an assessment shall provide necessary feedback to the all the relevant administrative authorities and energy critical entities, regarding the current preparedness level and response capability. The authors hope that the presented methodological approach will be applicable and aligned to the legal environment of other EU member states too.

Funding

This work was supported by the Ministry of the Interior of the Czech Republic [grant number VK01030014].

Glossary of Most Important Terms

Critical Infrastructure means an asset, a facility, equipment, a network or a system, or a part of an asset, a facility, equipment, a network or a system, which is necessary for the provision of an essential service [1].

Critical Entity means a public or private entity which has been identified by a Member State as belonging to one of

the categories set out in the Directive (EU) 2022/2557 of the European Parliament and of the Council [1].

Critical Infrastructure Resilience is the ability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event (i.e. incident or disaster) [3].

Disaster is a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability, and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts [41].

Disaster Preparedness are the knowledge and capacities developed by governments, response and recovery organizations, communities and individuals to effectively anticipate, respond to and recover from the impacts of likely, imminent or current disasters [41].

Essential Service means a service which is crucial for the maintenance of vital societal functions, economic activities, public health and safety, or the environment [1].

External Resilience of the Critical Infrastructure is the ability of the territorial unit on which the affected critical infrastructure element is located to respond to disasters. It is therefore a set of all factors influencing the preparation and resolving of disasters in relation to the critical infrastructure element. However, these factors cannot be influenced by the critical infrastructure element, as they are conditioned by its environment [42].

Incident means an event which has the potential to significantly disrupt, or that disrupts, the provision of an essential service, including when it affects the national systems that safeguard the rule of law [1].

Internal Resilience of the Critical Infrastructure is the ability of the critical infrastructure to reduce the

magnitude and/or duration of disruptive events, i.e. incidents or disasters [3].

Territorial Unit is, in the context of this chapter, a municipality which is defined as the basic territorial community of citizens and has the right to govern itself [43].

References

1. Directive (EU) (2022) Directive (EU) 2022/2557 of the European Parliament and of the Council of 14 December 2022 on the resilience of critical entities and repealing Council Directive 2008/114/EC
2. Rehak D, Senovsky P, Slivkova S (2018) Resilience of critical infrastructure elements and its main factors. *Systems* 6(2):21. <https://doi.org/10.3390/systems6020021> [Crossref]
3. National Infrastructure Advisory Council (2009) Critical infrastructure resilience final report and recommendations. U.S. Department of Homeland Security, Washington, DC
4. Echave C (2022) Territorial resilience: pillars for a holistic approach of resilience for land use planning. Euro-Mediterranean Economists Association, Barcelona
5. Brunetta G, Ceravolo R, Barbieri CA, Borghini A, de Carlo F, Mela A, Beltramo S, Longhi A, De Lucia G, Ferraris S, Pezzoli A, Quagliolo C, Salata S, Voghera A (2019) Territorial resilience: toward a proactive meaning for spatial planning. *Sustainability* 11(8):2286. <https://doi.org/10.3390/su11082286> [Crossref]
6. Petit F, Bassett G, Black R, Buehring W, Collins M, Dickinson D, Fisher R, Haffenden R, Huttenga A, Klett M, Phillips J, Thomas M, Veselka S, Wallace K, Whitfield R, Peerenboom J (2013) Resilience measurement index: an indicator of critical infrastructure resilience. Argonne National Laboratory, Lemont, IL
7. Prior T (2015) Measuring critical infrastructure resilience: possible indicators (Risk and Resilience Report 9). Eidgenössische Technische Hochschule, Zurich
8. Bertocchi G, Bologna S, Carducci G, Carrozzi L, Cavallini S, Lazari A, Oliva G, Trabalesi A (2016) Guidelines for critical infrastructure resilience

- evaluation. Italian Association of Critical Infrastructures' Experts, Roma
9. Nan C, Sansavini G (2017) A quantitative method for assessing resilience of interdependent infrastructures. *Reliabil Eng Syst Saf* 157:35–53. <https://doi.org/10.1016/j.res.2016.08.013> [Crossref]
 10. Cai B, Xie M, Liu Y, Liu Y, Feng Q (2018) Availability-based engineering resilience metric and its corresponding evaluation methodology. *Reliabil Eng Syst Saf* 172:216–224. <https://doi.org/10.1016/j.res.2017.12.021> [Crossref]
 11. Rehak D, Senovsky P, Hromada M, Lovecek T (2019) Complex approach to assessing resilience of critical infrastructure elements. *Int J Crit Infrastruct Protect* 25:125–138. <https://doi.org/10.1016/j.ijcip.2019.03.003> [Crossref]
 12. Carmeli A, Schaubroeck J (2008) Organisational crisis-preparedness: the importance of learning from failures. *Long Range Plan* 41(2):177–196. <https://doi.org/10.1016/j.lrp.2008.01.001> [Crossref]
 13. Hede S (2017) Perceptions of crisis preparedness and motivation: a study among municipal leaders. *Saf Sci* 95:83–91. <https://doi.org/10.1016/j.ssci.2017.02.010> [Crossref]
 14. Drennan LT, McConnell A, Stark A (2014) Risk and crisis management in the public sector. Routledge, London. <https://doi.org/10.4324/9781315816456>
 15. Lerbinger O (2012) The crisis manager: facing disasters, conflicts, and failures. Routledge, London [Crossref]
 16. Kapucu N, Özerdem A, Sadiq AA (2011) Managing emergencies and crises: global perspectives, 2nd edn. Jones & Bartlett Learning, Burlington, MA
 17. Howitt AM, Leonard HB (2009) Managing crises: responses to large-scale emergencies. CQ Press, Washington, D.C.
 18. Rehak D, Hromada M, Lovecek T (2020) Personnel threats in an electric power critical infrastructure sector and their impacts on dependent sectors. *Saf Sci* 127:104698. <https://doi.org/10.1016/j.ssci.2020.104698> [Crossref]
 19. PPD-21 (2013) Presidential policy directive: critical infrastructure security and resilience. The White House, Washington, DC

20. Clark RM, Hakim S (2017) Cyber-physical security: protecting critical infrastructure at the state and local level. Springer, Cham. <https://doi.org/10.1007/978-3-319-32824-9>
21. Monstadt J, Schmidt M (2019) Urban resilience in the making? The governance of critical infrastructures in German Cities. *Urban Stud* 56(11):2353–2371. <https://doi.org/10.1177/0042098018808483> [Crossref]
22. Novotny P, Janosikova M (2020) Designating regional elements system in a critical infrastructure system in the context of the Czech Republic. *Systems* 8(2):13. <https://doi.org/10.3390/systems8020013> [Crossref]
23. Rehak D, Markuci J, Hromada M, Barcova K (2016) Quantitative evaluation of the synergistic effects of failures in a critical infrastructure system. *Int J Crit Infrastruct Protect* 14:3–17. <https://doi.org/10.1016/j.ijcip.2016.06.002> [Crossref]
24. Mitsova D, Sapat A, Esnard AM, Lamadrid AJ (2020) Evaluating the impact of infrastructure interdependencies on the emergency services sector and critical support functions using an expert opinion survey. *J Infrastruct Syst* 26(2):548. [https://doi.org/10.1061/\(ASCE\)IS.1943-555X.0000548](https://doi.org/10.1061/(ASCE)IS.1943-555X.0000548) [Crossref]
25. Rehak D, Novotny P (2016) Bases for modelling the impacts of the critical infrastructure failure. *Chem Eng Trans* 53:91–96. <https://doi.org/10.3303/CET1653016> [Crossref]
26. Labaka L, Hernantes J, Sarriegi JM (2016) A holistic framework for building critical infrastructure resilience. *Technol Forecast Soc Change* 103:21–33. <https://doi.org/10.1016/j.techfore.2015.11.005> [Crossref]
27. Labaka L, Hernantes J, Sarriegi JM (2015) Resilience framework for critical infrastructures: an empirical study in a nuclear plant. *Reliabil Eng Syst Saf* 141:92–105. <https://doi.org/10.1016/j.res.2015.03.009> [Crossref]
28. Labaka L, Comes T, Hernantes J, Sarriegi JM, Gonzalez JJ (2014) Implementation methodology of the resilience framework. In: *Proceedings of the 47th Hawaii international conference on system sciences, Waikoloa, HI*, pp 139–148. <https://doi.org/10.1109/HICSS.2014.26>
29. Petersen L, Lange D, Theocharidou M (2020) Who cares what it means? Practical reasons for using the word resilience with critical infrastructure

- operators. *Reliabil Eng Syst Saf* 199:106872. <https://doi.org/10.1016/j.res.2020.106872> [Crossref]
30. Nipa TJ, Kermanshachi S, Ramaji I (2019) Comparative analysis of strengths and limitations of infrastructure resilience measurement methods. In: *Proceedings of the 7th CSCE international construction specialty conference (ICSC)*, Laval, Greater Montreal, 12–15 June 2019, pp 2921–2929
31. L’Heureux AV, Therrien MC (2013) Interorganizational dynamics and characteristics of critical infrastructure networks: the study of three critical infrastructures in the greater Montreal area. *J Contingen Crisis Manag* 21(4):211–224. <https://doi.org/10.1111/1468-5973.12030> [Crossref]
32. Shaw D, Scully J, Hart T (2014) The Paradox of social resilience: how cognitive strategies and coping mechanisms attenuate and accentuate resilience. *Global Environ Change* 25:194–203. <https://doi.org/10.1016/j.gloenvcha.2014.01.006> [Crossref]
33. Mees B, McMurray A, Chhetri P (2016) Organisational resilience and emergency management. *Austr J Emerg Manag* 31(2):38–43
34. Lundberg J, Johansson BJE (2019) Resilience is not a silver bullet: harnessing resilience as core values and resource contexts in a double adaptive process. *Reliabil Eng Syst Saf* 188:110–117. <https://doi.org/10.1016/j.res.2019.03.003> [Crossref]
35. Quiroz-Palma P, Penadés MC, Núñez AG (2020) Resilience learning for emergency plan management in organizations. In: *Proceedings of the 17th international conference on information systems for crisis response and management (ISCRAM)*, Blacksburg, VA, pp 558–567
36. Kapucu N, Ge YG, Martín Y, Williamson Z (2021) Urban resilience for building a sustainable and safe environment. *Urban Govern* 1(1):10–16. <https://doi.org/10.1016/j.ugj.2021.09.001> [Crossref]
37. Dormady NC, Greenbaum RT, Young KA (2021) Value of information on resilience decision-making in repeated disaster environments. *Nat Hazards Rev* 22(1):415. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000415](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000415) [Crossref]
38. Münch C, Hartmann E (2023) Transforming resilience in the context of a pandemic: results from a cross-industry case study exploring supply chain

viability. Int J Product Res 61(8):2544–2562. <https://doi.org/10.1080/00207543.2022.2029610>
[Crossref]

39. Bernatik A, Senovsky P, Senovsky M, Rehak D (2013) Territorial risk analysis and mapping. Chem Eng Trans 31:79–84. <https://doi.org/10.3303/CET1331014>
[Crossref]
40. Saaty TL (2008) Decision making with the analytic hierarchy process. Int J Serv Sci 1(1):83–98. <https://doi.org/10.1504/IJSSCI.2008.017590>
[Crossref]
41. UNDRR (2017) Sendai framework terminology on disaster risk reduction. United Nations Office for Disaster Risk Reduction, Geneva. <https://www.undrr.org/terminology>. Accessed 17 Dec 2023
42. Liu JWJ, Reed M, Girard TA (2017) Advancing resilience: an integrative, multi-system model of resilience. Person Individ Differ 111:111–118. <https://doi.org/10.1016/j.paid.2017.02.007>
[Crossref]
43. ECR (2015) Local and regional government levels in the EU. European Committee of the Regions, Brussels. <https://doi.org/10.2863/874020>

Enhancing Resilience of Active Distribution Networks to Extreme Weather Events Now and in the Future

Laiz Souto¹  and Abdualлах Al-Mashhadani^{1, 2}

(1) Department of Electronic and Electrical Engineering,
University of Bath, Bath, UK

(2) Faculty of Science and Engineering, University of
Bristol, Bristol, UK

 **Laiz Souto**

Email: lsdc21@bath.ac.uk

Abstract

Decarbonization, climate change, and digitalization are bringing significant changes to electrical power systems worldwide. In this ever-changing scenario, power distribution networks are evolving from passive to active, with an increasing uptake of low carbon distributed energy resources and information and communication technologies; and also increasingly vulnerable to different types of severe weather events, thanks to an increasing dependency on electricity for the well-functioning of economies and societies worldwide. In this context, this chapter describes how active power distribution networks

can take advantage of distinct capabilities to maintain or improve their resilience to different severe weather event categories. It considers different resilience enhancement strategies and enabling technologies along with implementation timescales suitable for resilience planning and operational measures. Current challenges to ensure that active power distribution networks remain resilient to different types of severe weather events are also discussed. These aspects are embedded into an optimization problem formulation aimed at improving the network operating performance under severe weather conditions, making use of distributed energy resources for resilience enhancements over different timescales. The methodology is demonstrated in a realistic distribution network in the United Kingdom, with simulation results showing the resilience enhancement benefits provided by these technologies.

Keywords Active power distribution networks – Climate change – Climate change adaptation – Climate change mitigation – Distributed energy resources – Distributed generation – Electric vehicles – Energy storage systems – Extreme weather – Flexibility services – Flexible loads – Natural hazards – Power distribution networks – Power system faults – Renewable energy – Resilience – Smart grids

Abbreviations

AMI Advanced metering infrastructure

DER Distributed energy resource

DSM Demand side management

DSO Distribution system operator

ENS Energy not supplied

EV Electric vehicle

HOP Hybrid open point
ICT Information and communication technologies
IoT Internet of things
LV Low voltage
MES Multi-energy system
PMU Phasor measurement unit
PV Photovoltaic
p.u. Per unit
SCADA Supervisory control and data acquisition
SOP Soft open point
VPP Virtual power plant
UK United Kingdom

1 Introduction

Power distribution networks have a prominent role in the energy transition towards a resilient net zero future—evolving from passive to active distribution networks, thanks to an increasing uptake of ICT together with distributed energy resources and flexibility options at distinct distribution voltage levels. The importance of active distribution networks is expected to increase even further in the next few years, thanks to an increasing electrification of different economy sectors aligned with net zero carbon emissions targets. In this scenario, planning and operational practices adopted by DSOs must be upgraded to ensure a satisfactory level of electricity service provision while successfully accommodating new energy technologies now and in the future. To achieve this, however, DSOs must also account for current and projected risks associated with a changing climate for their business.

In comparison with transmission systems, power distribution networks are much more vulnerable to different severe weather event categories, for their less robust design and operational requirements. Consequently, power distribution network components are more prone to be damaged under severe weather conditions than their transmission system counterparts. The impacts of disruptive weather on distribution networks will be worsened even further as electrification of different economy sectors and renewable energy penetration levels increase in the next few years. Firstly, for the increasing requirements for power grid infrastructure, especially at distribution voltage levels, where these new clean energy technologies will be connected to the grid. Secondly, for the increasing electrical load demand, which is also weather dependent (e.g., heating and cooling). Thirdly, for the increasing uptake of intermittent renewable generation (e.g., wind turbines, solar PV panels), which is not only weather dependent, but also outdoors—hence, directly influenced by and exposed to a range of weather conditions. Thereby, active distribution network upgrades bring significant challenges for a resilient design and operation of distribution networks.

Despite these challenges, the increasing uptake of ICT and flexibility resources also bring great opportunities to maintain or improve resilience of active distribution networks to distinct severe weather event categories. These technologies may contribute to embed resilience principles into different design and operational practices adopted by DSOs, such as grid reinforcement, maintenance, and restoration tasks. To achieve this, the benefits provided by these technologies (e.g., performance enhancements and cost effectiveness) must be thoroughly assessed over a range of scenarios defining normal operation and exceptional circumstances. By adopting appropriate resilience planning and operational measures,

DSOs will ensure satisfactory levels of quality and availability of service to different economy sectors now and in the future.

In this context, this chapter describes how active power distribution networks can take advantage of distinct capabilities to maintain or improve their resilience to different severe weather event categories—also defined as high impact, low probability events or exceptional circumstances. It considers different resilience enhancement strategies and enabling technologies along with implementation timescales suitable for resilience planning and operational measures. These aspects are embedded into an optimization problem formulation aimed at improving the network operating performance under severe weather conditions, making use of resources typically available in active distribution networks for resilience enhancements over different timescales.

The rest of this chapter is structured as follows. Section 2 provides a background on active distribution networks and resilience assessment in power grids. In Sect. 3, implementation timescales suitable for resilience planning and operational measures are considered along with different enabling technology options. Next, Sect. 4 discusses existing challenges to ensure that active power distribution networks remain resilient to different severe weather event categories. In Sect. 5, an optimization problem formulation aimed at improving the network operating performance under severe weather conditions is presented, taking advantage of mobile energy resources for resilience enhancements. Afterwards, Sect. 6 presents a test case along with simulation results and discussions. Finally, Sect. 7 concludes the chapter and provides further perspectives.

2 Background

This section provides an overview of key concepts related to active distribution networks and resilience assessment in power systems, required to get through the rest of the text.

2.1 Key Elements of Active Distribution Networks

Thanks to an increasing uptake of distributed energy resources, flexible topologies, and ICT, power distribution networks are evolving from passive to active. This section describes key elements of active distribution networks, as well as changes in operating conditions introduced by these emerging technologies. Table 1 summarizes the key differences between modern active distribution networks and conventional passive distribution networks. For more details, refer to [1–5].

Table 1 Key differences between features of active and passive distribution networks

Key feature	Active distribution network	Passive distribution network
ICT	Present	Absent
DERs	In communication with the network and mostly present	Not in communication with the network and mostly absent
Network reconfiguration	Automatic and remote	Manual and on site
Flexible loads	Present or can be enabled	Absent and cannot be enabled
MES couplings	Optimal couplings	Couplings cannot be optimized

2.1.1 Information and Communication Technologies

Active distribution networks take advantage of ICT in different ways to deliver satisfactory levels of reliability and quality of supply [1, 2]. They are equipped with advanced

monitoring and control system solutions which improve exchange, processing, and usage of different pieces of information over relevant short-term operational timescales—from hours ahead to real time. Some examples of ICT in active distribution networks are described as follows:

- AMI systems provide smart meter data to DSOs in (near) real time for demand monitoring, which facilitates DSM and fault localization in active distribution networks;
- SCADA systems are able to monitor and control the status of network components in near real time, which facilitates fault detection and localization for subsequent fault isolation and network recovery;
- PMUs provide voltage and current synchrophasors (i.e., magnitudes and phase angles of synchronized electrical phasor quantities) at very high sampling rates (higher than SCADA systems) for network operation monitoring, with accuracy in the order of microsecond;
- VPPs aggregate several units (hundreds or even thousands) of small-scale DERs into a single commercial unit (i.e., appearing as a single supplier to the DSO and in the wholesale electricity market), providing communication with and control of each generating unit in real time;
- EV charging infrastructure provides facilitates power exchanges between EVs and the distribution network, providing communication with and control of connected EVs through charging (grid-to-vehicle) and discharging (vehicle-to-grid);
- Internet of Things (IoT) sensors and devices play an important role in collecting different source of data, such as weather conditions and operating status of energy appliances, to improve the network performance and keep operation within acceptable limits.

In contrast, passive distribution networks have very small or limited presence of ICT in advanced monitoring

and control systems. This limitation prevents DSOs from accessing (near) real-time information about the network operating conditions and component status which could be used to improve their short-term operational performance. Hence, the lack of (near) real-time data acquisition, monitoring, and control capabilities in passive networks hinder DSOs in their efforts to improve supply service provision—with negative effects on reliability and resilience. Upgrading these networks to increase presence of ICT will positively contribute to improve their resilience. For instance,

- By facilitating DSM and fault localization, AMI provides an indication of the requirements for network repair and restoration services, such as repair crews and emergency generators;
- By monitoring and controlling the status of network components, SCADA systems facilitate accurate identification of network faults for allocation of repair and restoration services;
- By collecting synchrophasor measurements, PMUs facilitate fast and accurate identification of system disturbances for the implementation of emergency and recovery actions;
- By aggregating several small-scale DERs into a single entity, VPPs reduce supply fluctuations which might lead to power quality and stability problems with cascading system effects;
- By controlling EV charging and discharging, an EV infrastructure is able to provide grid support services during emergencies;
- By collecting different sources of data, IoT devices provide an indication of locations and parts of the network at high (or higher) risk of faults.

It is noteworthy that controllers are much more modern and sophisticated in active distribution networks than in

passive distribution networks, thanks to the availability of ICT. Passive distribution networks use manual controllers for different tasks, which usually take more time and are prone to human errors. In active distribution networks, controllers handle (near) real-time information about energy generation and consumption, measurements of electrical quantities, weather observations, among others. Hence, they play a vital role in managing the active distribution networks, through automatic monitoring, analysis and support for decision making.

2.1.2 Distributed Energy Resources

Active distribution networks have large-scale DER penetration, which play a key role in the provision of clean energy and flexibility. These resources typically comprise intermittent renewable generation, such as wind turbines and solar PV panels, and battery energy storage systems. In the last few decades, these resources became technologically competitive and financially affordable for different applications, which led to an increasing uptake from utility to household level.

The increasing uptake of these energy technologies at different scales and voltage levels brings challenges and opportunities for DSOs [3]. On one hand, they contribute to reduce carbon emissions from the energy sector, provide flexibility benefits for the distribution network, and are driving decarbonization of other economy sectors through electrification. On the other hand, they require significant changes in the design and operation of distribution networks to withstand disruptions to infrastructure and supply service provision (e.g., caused by bidirectional power flows, low inertia, wind and solar intermittence, infrastructure damage to outdoor network components).

These challenges and opportunities are inexistent in passive distribution networks. On one hand, they are designed and operated for unidirectional power (flows from

large-scale power plants to end users), relying on synchronous generators (conventional sources of grid inertia and constant baseload) not directly exposed to the environment. On the other hand, they have limited potential to achieve decarbonization and help other economy sectors to decarbonize through electrification, for the centralized design and operation approaches. Furthermore, the benefits provided by DERs are limited without integration with ICT, for the required monitoring and control capabilities.

In this context, VPP developments facilitate uptake of DERs in active distribution networks, by aggregating several units into a single commercial unit [1]. The VPP controller has downward links with each generating unit for real-time communication and control, which reduces supply fluctuations and increases predictability and dispatchability of energy resources. VPPs also increase visibility of DERs for the DSO, as each VPP appears as a single supplier.

2.1.3 Network Reconfiguration

Active distribution networks can take advantage of automatic network reconfiguration to improve their operating performance in response to changes in operating conditions, such as generation and demand profiles and network disturbances [1, 2]. Automatic network reconfiguration includes dynamic real-time adjustments of network topology, such as opening and closing switches and circuit breakers, transformer tap changes, SOPs and HOPs [4].

Automatic network reconfiguration actions can benefit DSOs in different ways. For example, by improving the network's ability to withstand disturbances (e.g., through a sequence of reconfiguration actions for fault isolation and electricity rerouting), it enhances its resilience and reliability to external events; by selecting the shortest

electrical distance of power flows from generation to loads (e.g., through a sequence of reconfiguration actions for minimizing electrical distances), it minimizes power losses and increases the network efficiency; by facilitating an effective DER allocation (e.g., through a sequence of reconfiguration actions for voltage regulation, reactive power compensation, and power balancing), it contributes to reduce network congestion and maintain stability while increasing utilization of low carbon energy resources. To this extent, implementation of SOPs and HOPs also contributes to increase the network capacity and availability of supply—and to postpone investments in capacity expansion associated with the construction of new lines and commissioning of new generation units.

In contrast, network reconfiguration actions in passive distribution networks rely on manual methods, including opening and closing switches and circuit breakers and transformer tap changes. These manual reconfiguration actions are typically less frequent and linked to corrective actions (e.g., in the event of an outage) rather than performance improvement actions (e.g., to improve efficiency or resilience). However, these manual methods present important drawbacks, notably slower execution times and increased likelihood of human errors which may lead to cascading network effects and major power outages. This difference between automatic and manual reconfiguration actions is mainly attributed to the lack of real-time monitoring and control capabilities in passive networks, which prevents automatic methods.

2.1.4 Flexible Loads

Active distribution networks can also benefit from flexible loads to increase utilization of renewable energy and reduce network congestion and peak loads [1]. Load-shifting of flexible loads to periods of higher renewable energy generation, reduced network congestion, and lower

demand requirements improves efficiency, reliability, and resilience of the network. This is made possible by advanced ICT, such as AMI systems, to manage demand and DERs along with electricity tariffs. This approach also enables customers to actively participate in demand reduction and load shifting initiatives and gain control over their energy usage and behavioral patterns.

Hence, the introduction of flexible loads contributes not only to optimize operation of active distribution networks, but also to empower customers in their energy choices.

This approach cannot be realized in passive distribution networks, for the lack of advanced monitoring and control capabilities to enable load demand flexibility. As a result, demand reduction and load shifting initiatives are restricted in passive distribution networks, as well as benefits for DSOs and customers. This limitation has important implications for different customer categories, especially for critical loads associated with other critical infrastructure and services plus vulnerable customers and customer groups. As load flexibilization cannot be achieved, critical loads are at a higher risk of supply interruption in the event of an outage or system disturbance leading to disconnection.

2.1.5 Multi-Energy System Couplings

The integration of different energy carriers, such as electricity, gas, heating and cooling, provides additional benefits for the resulting Multi-Energy System (MES) in terms of flexibility, efficiency, reliability and resilience [5]. Thanks to these sector couplings, the resulting system is provided with additional energy generation and transportation options which would not be implementable otherwise (e.g., for financial or time constraints). Some examples of enabling technologies include heat pumps to convert electricity to heat, power-to-gas facilities (e.g., electrolyzers) to convert electricity surplus to gas, and

vehicle-to-grid technologies to convert electrochemical storage to electricity.

Active distribution networks can maximize benefits derived from MES couplings, thanks to the availability of ICT through advanced monitoring and control systems. These technologies can facilitate energy conversion as needed to reduce energy imbalances and the impact of disturbances on the resulting system while also increasing renewable energy utilization and flexibility options.

2.2 Resilience Assessment in Power Systems

This section describes key aspects of resilience assessment and enhancement decisions in active distribution networks. The following paragraphs cover definitions, quantification, and methods for resilience enhancements in active distribution networks. For more details, refer to [6–9].

2.2.1 Definition

In this chapter, resilience is defined as the system's ability to anticipate, respond to, and recover from external high impact, low probability events, such as severe weather, natural hazards, and cyber-attacks [6, 7]. The main attributes of a resilient power system are robustness, resourcefulness, rapid recovery, and adaptability [8]. These attributes are critical to maintaining quality of supply and minimizing performance degradation.

An illustrative example of a resilience curve based on the system's ability to anticipate, respond to, and recover from external high impact, low probability events is shown in Fig. 1, considering the disaster-relative periods suggested by [7, 10]. Note that other more specific temporal classifications of resilience-oriented planning and operational strategies can be embedded into this conceptual resilience curve (see [6, 7] for more details).

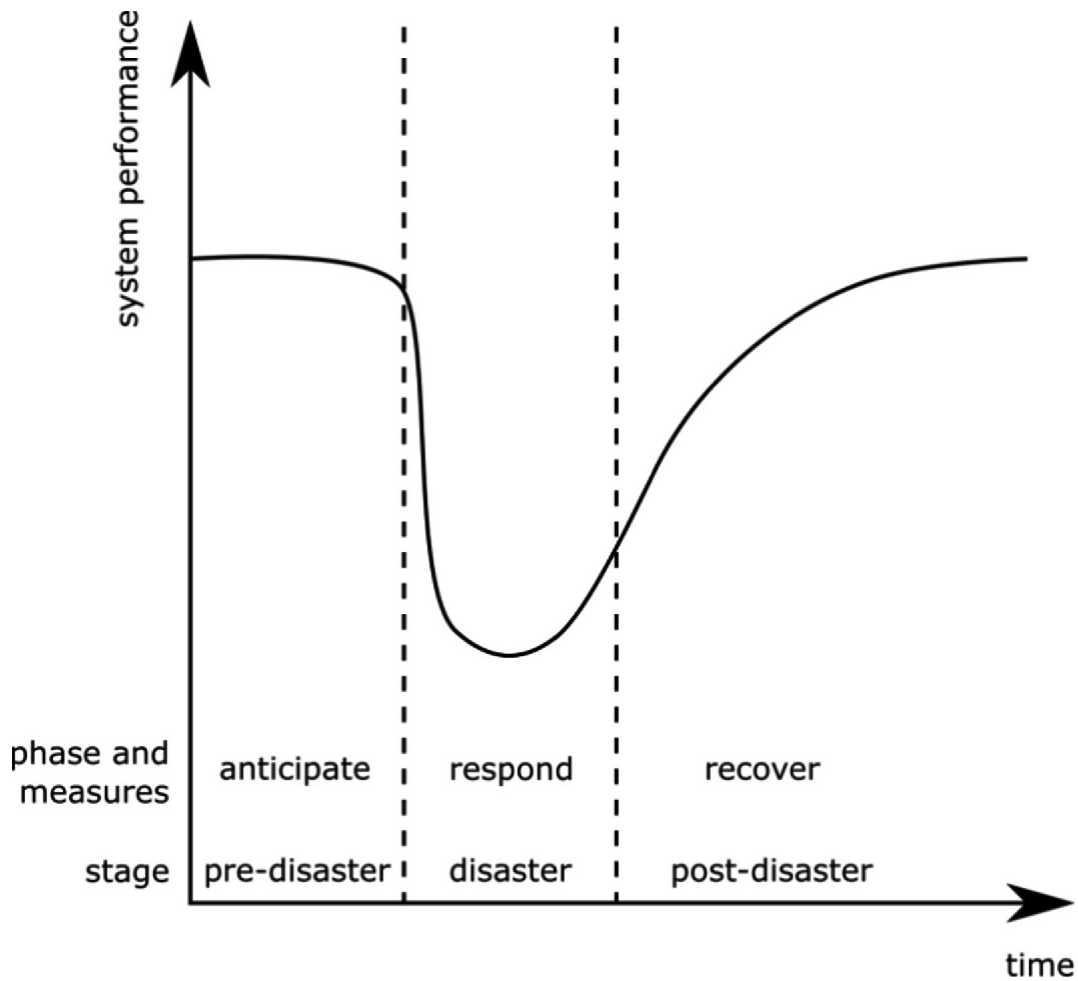


Fig. 1 Generic resilience curve divided into three main conceptual stages according to the disaster-relative period, phase and measures. The curve shows the system performance degradation (y-axis) evolving over time (x-axis)

Here it is important to distinguish between high impact, low probability events in the scope of resilience and low impact, high probability events in the scope of reliability. Disruptions associated with resilience problems are characterized by extensive network damage and collapse, which are excluded from the DSO performance figures. In turn, disruptions associated with reliability problems are characterized by few uncorrelated failures of network components, which are accounted for in the DSO performance indicators. It is noteworthy that power system failures attributed to a specific cause do not necessarily fall

exclusively into reliability or resilience problems, as this depends on their impacts on infrastructure and service.

2.2.2 Quantification

Power system resilience encompasses different aspects of power grid infrastructure and service provision under exceptional circumstances. Consequently, power system resilience can be quantified as a function of disruptions to infrastructure and service provision caused by external high impact, low probability events [10]. On one hand, metrics to quantify infrastructure resilience relate to the physical integrity and mechanical strength of infrastructure components, such as lines and poles; on the other hand, metrics to quantify electricity service provision relate to quality and continuity of supply to the customers. An illustrative example of a resilience curve showing different energy dimensions of resilience is shown in Fig. 2, considering the definitions of resilience adopted in this chapter.

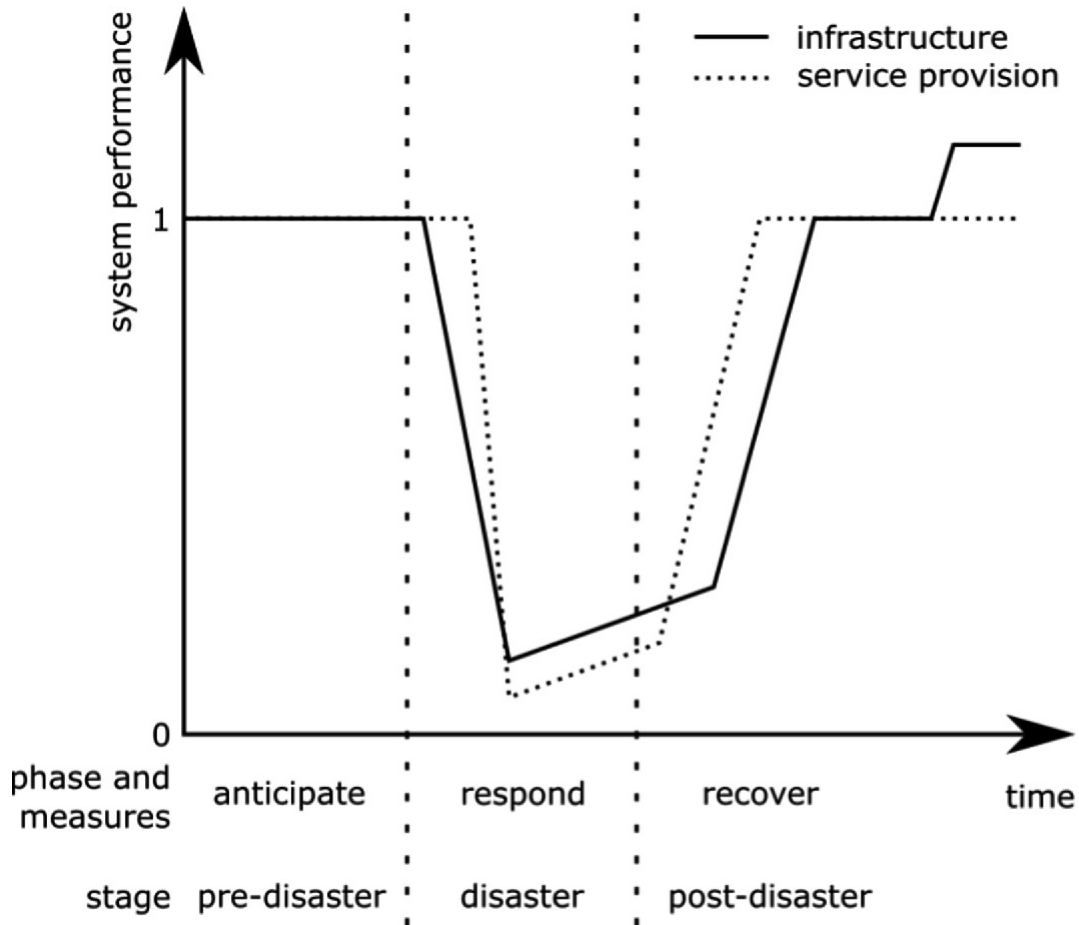


Fig. 2 Generic resilience curve showing the energy dimensions of resilience as a function of the disaster-relative period, phase and measures. The curve shows the system performance degradation (y-axis) in terms of disruptions to infrastructure (solid line) and service provision (dashed line) over time (x-axis)

There are different metrics to quantify the performance of power grid infrastructure and service provision.

However, there is no consensus about the definition and usage of specific metrics to quantify resilience of power systems to different types of high impact, low probability events [9]. This is attributed to the overlapping with metrics commonly used to quantify other planning and operational aspects of power systems, such as reliability and energy security. In this context, it is of paramount importance to distinguish between energy security, reliability, and resilience problems and events of interest for an appropriate assessment of the system requirements.

2.2.3 Methods

Improvements in power system resilience to extreme weather events may combine different measures implementable over different timescales, from long-term planning several years in advance to real-time operation and post-event recovery. Thus, the selection of the most appropriate measures depend on the available resources and remaining time for the expected impacts on the system.

Resilience assessment methods can take advantage of different metrics to quantify the network performance in terms of disruptions to infrastructure and service provision. The outcomes of this analysis are then used to identify appropriate resilience enhancement measures to improve the network performance—and maintain or improve resilience of infrastructure and service provision based on target or achievable performance metrics.

The selection of appropriate measures to enhance power system resilience to severe weather events is typically based on centralized robust optimization, as this is relevant for high impact, low probability events. Robust optimization problems are defined over a range of scenarios—with different probabilities of occurrence and realizations of control parameters—to ensure robustness of the solution in terms of optimality and feasibility (see e.g., [11, 12]).

Distributed optimization methods are relevant to accommodate information from multiple sources in large-scale networks and break the main optimization problem into tractable subproblems with information exchange (see e.g., [13]). Distributed optimization is also useful to conceal conflicting interests between different subproblems (e.g., owners of generation and flexibility assets and customers). Thanks to the availability of ICT in active distribution networks, the adoption of distributed optimization methods is made possible.

In comparison with centralized optimization, the quality of the solution obtained with distributed optimization is worse, as it does not necessarily corresponds to the global optimal solution. Thus, centralized optimization methods are preferred in situations in which a globally optimal solution is required, such as long-term investment planning decisions for electricity networks. Conversely, centralized optimization methods are less scalable to complex large-scale problems, for which distributed optimization provides an alternative. Hence, distributed optimization methods are useful in situations in which scalability is critical, such as near real-time operational decisions in large-scale distribution networks.

3 Key Strategies for Weather- and Climate-Resilient Active Distribution Networks

Improvements in power system resilience to extraordinary events may combine different planning and operational measures implementable over different timescales. Resilience planning typically involve infrastructure hardening and upgrades, whereas operational resilience typically consist of network reconfiguration, generation re-dispatching, and usage of flexibility energy resources. In this context, this section describes key strategies for resilience enhancements in active distribution networks to severe weather events, considering contributions from emerging technologies, such as distributed energy resources, flexibility options, and ICT. Relevant planning and operational strategies for enhancing power system resilience to different severe weather event categories are described as follows. For more information, refer to [14].

3.1 Hardening Strategies

Hardening strategies for resilience enhancements in active distribution networks are envisaged to strengthen the physical infrastructure against extreme weather events, as well as natural disasters and projected climate change. Key elements of the distribution network include lines, poles, towers, substations, transformers, switchgear, and DERs which should be designed to withstand the impacts of different severe weather event categories.

Among different severe weather event categories, floodings are particularly problematic for power system infrastructure and operations, as they may take several days to be cleared. Hence, enhancing the resilience of the active distribution network to flooding is crucial, especially in regions with an expected increase in associated risks due to climate change. Hardening measures against flooding may include a combination of flooding barrier installation around important equipment (e.g., substations, transformers, and switchgear), improvements in drainage systems, and elevation or relocation of critical equipment (e.g., substations) if necessary.

Hardening strategies are also important for other severe weather event categories, such as wind, snow and ice, as well as compound storms involving multiple hazards. Strengthening the foundations or structural elements of poles, towers, and overhead lines to withstand high winds, snow and ice can reduce their probability of failure and improve network resilience.

Droughts can also have negative impacts on the resilience of underground components, such as cables, and on the foundations of ground-mounted components, such as poles and towers. Shrinkage and expansion of the soil during drought and rainfall, respectively, lead to ground movement, which may deform underground cables and destabilize foundations of ground-mounted components. Expanding and strengthening underground cable paths and

strengthening component foundations can improve the resilience of the network.

In active distribution networks, strengthening structural elements of distributed energy resources, such as wind turbines, solar PV panels, and EV charging stations, can also have resilience benefits. In comparison with conventional networks, active distribution networks have an increased exposure to severe weather events, as intermittent renewable generation units must be installed outdoors.

3.2 Smart Operational Strategies

Operational strategies for resilience enhancements in active distribution networks are envisaged to improve their short-term operating performance before, during, and after extreme weather events. These strategies may combine generation redispatch, network reconfiguration, and pertinent adjustments in the operating conditions of the network (e.g., changes in component status). In active distribution networks, ICT availability can turn these operational strategies into smart operational strategies, taking advantage of different pieces of information about the network (e.g., measurements of electrical quantities, weather forecasts). Thanks to information exchanges and automatic control actions, these enhanced monitoring and control capabilities facilitate implementation of preventive, emergency, and recovery plans, as well as utilization of DERs and flexibility options.

During hazards, DSOs are able to operate active networks remotely, thanks to their advanced monitoring and control capabilities. By remotely operating their network, DSOs can improve their emergency plans and recovery actions in different ways. For instance, SCADA and PMUs provide useful information about network faults, which can be used to accelerate fault clearance and network recovery actions in the aftermath of severe

weather events (e.g., high winds, snow and ice). In turn, AMI systems provide useful information about generation and consumption at customer level, which can also be used in certain situations to disconnect loads (e.g., to prevent overloading and the risk of electric fires during a heatwave) and assist evacuation of affected areas (e.g., in the event of a flooding). The information collected by AMI systems and IoT devices also facilitates energy management and forecasting. Furthermore, smart meters in AMI systems also enable customers to actively monitor their energy consumption and participate in reducing or shifting their demand (e.g., EV charging and interruptible loads).

Increasing uptake of DERs and flexibility resources along with advanced monitoring and control capabilities also facilitates dynamic and adaptable reconfiguration of active distribution networks under severe weather conditions. This approach enables DSOs to maintain availability of supply through local power balancing services (e.g., as in a microgrid). For it to be possible, DSOs can also take advantage of pre-positioning and dispatch of mobile generation and storage units to increase availability of resources. These approaches can also be implemented within a VPP to ensure communication with several generating units and increase predictability of supply in combination with other DERs.

4 Challenges

This section describes current and emerging challenges posed by decarbonization, severe weather events and climate change to active distribution networks. For more details, refer to [14, 15].

4.1 Decarbonization

Decarbonization efforts are increasing uptake of renewable energy sources, especially from wind and solar, for their widespread availability, maturity, and affordability for electricity generation. In turn, the availability of mature and affordable technologies for low carbon electricity generation is driving electrification of other economy sectors in the pursuit of decarbonization targets. This situation poses significant challenges for active distribution networks, as electrical load demand and reliance on power distribution networks will increase and incentivize uptake of DERs even further.

Intermittent renewable generators have different characteristics from conventional fossil fuel fired power plants. As they are inverter interfaced, they do not provide inertia to the network, which affects the network's ability to compensate for power imbalances and voltage and frequency deviations. As they provide variable supply outputs, they are unable to provide a baseload power supply and cannot be dispatched as individual units (which can be overcome by VPP developments). Furthermore, the increasing integration of DERs in the distribution network poses additional challenges associated with bidirectional power flows, voltage regulation, power balancing and power quality problems.

Electrification of different economy sectors is increasing reliance on power systems and distribution networks in particular, for the connection of different technologies at distribution voltage levels. Notably, decarbonization of the transport and the heat sectors are significantly increasing electrical load demand for the adoption of EVs and heat pumps. The resulting demand can increase above the maximum power ratings the distribution network components are designed for. It can also result in a significantly high coincident load demand (e.g., when many customers simultaneously charge their EVs and turn heat pumps on). This increased peak demand will require

massive upgrades on distribution networks – including new transformers, switchgear, underground cables, overhead lines etc.—such that it continues to operate within acceptable limits.

These changes bring important challenges for a resilient design and operation of distribution networks. To overcome these challenges, planning and operational practices should be adapted to effectively accommodate new technologies and an increasing demand for electricity towards a resilient net zero future. In addition, requirements for flexibility resources should be revised for stability and balancing services, especially when in combination with DERs. To achieve this, however, DSOs will need access to better weather and energy forecasts, especially for time-sensitive applications, as well as enhanced climate and energy models for long-term planning.

4.2 Extreme Weather Events in a Changing Climate

Climate change is believed to increase the severity (i.e., in terms of either or both frequency and intensity) of certain extreme weather event categories associated with power outages, such as storms, flooding, heatwaves, among others. Consequently, disruptions to power system infrastructure and service provision are likely to become more frequent and severe in a changing climate [16]. These disruptions will also negatively affect other critical infrastructure systems and services which rely on electricity, such as water, telecommunication, and transport sectors [17]. Table 2 summarizes key risks associated with severe weather events in a changing climate for active distribution networks. For more details, refer to [14].

Table 2 Key risks of severe weather events in a changing climate for active distribution networks

Severe weather event	Risk for active distribution network
Flooding, sea level rise, and coastal change	• Substations and EV chargers affected by sea flooding due to increased rainstorms, storm surges and/or tidal surges • Substations and EV chargers affected by river flooding due to increased rainfall • Substations and EV chargers affected by pluvial (flash) flooding due to increased rainstorms • Increased intensity of short duration rainfall leading to flooding • Fluvial river and coastal flooding of DSO sites or neighboring sites leaving DSO sites stranded • Saline contamination and increased corrosion rate of above and below ground assets from sea water or atmospheric salt • Ground contamination and transport of materials from flooding of contaminated sites
Raised temperatures and temperature cycles resources	• Overhead line conductors, transformers, and switchgear affected by temperature rise • Underground cable systems affected by increase in ground temperature • Substation and network earthing systems adversely affected by summer drought conditions • Demand growth in summer due to increased cooling load • Transformers affected by urban heat islands and coincident air conditioning demand • Above and below ground assets affected by lower temperatures and/or fast cycling between temperature extremes
Erosion and ground movement	• Overhead line structures and underground cable systems affected by summer drought and consequent ground movement • Structures affected by riverbank stability and scour, surface water runoff scour, groundwater geohazards, repeated cycles of drought and rainfall, landslips, slope stability and/or avalanche
Storms involving compound events	• Outdoor components more vulnerable to extreme weather events including a combination of wind, rainfall, snow or high/low temperature

Severe weather event	Risk for active distribution network
	• Outdoor components more vulnerable to warm wetter conditions combined with rainfall and/or wind • Operation affected by the “perfect storm” of a cold winter, high electricity demand and heavy persistent rain
Interdependencies	• Impacts on vegetation growth increasing interference to overhead lines • Impacts on transport infrastructure affecting the ability of crews from the DSO to reach critical assets • Impacts on communication systems affecting the flow of information from/to and response by the DSO • Impacts on asset management affecting the DSO’s ability to sufficiently mitigate climate risks that affect assets • Impacts on policy decisions affecting the use and operation of assets by the DSO

Left column lists different severe weather events of concern, whereas right column lists corresponding existing and projected risks

The risks described in Table 2 are aggravated by different resilience gaps associated with planning and operational practices adopted by DSOs. Inadequate planning occurs because of limited knowledge, models, and data about risks associated with natural hazards and/or limited resources to mitigate those risks. In turn, inadequate operation occurs because of ineffective preparedness plans to reduce performance degradation and/or limited resources that can be readily deployed for corrective actions in the network.

5 Materials and Methods

This section presents an optimization problem formulation aimed at minimizing performance degradation subject to operating and resource constraints over different timescales suitable for planning and operational decisions. The following paragraphs describe the problem formulation, including load demand, generation, storage, power flow, and resource constraints followed by the objective function. The mixed-integer quadratic programming framework described as follows is based on [12, 18], here adapted to other relevant planning and operational timescales.

5.1 Problem Setting

Consider a distribution network model defined by a set of buses (nodes) N , indexed by $n \in N$, and a set of branches (edges) E , indexed by $e \in E$. Time-varying quantities are defined over the horizon T , indexed by $t \in T$. Each bus has a time-varying active and reactive power supply denoted by p_{Gnt} and q_{Gnt} , load demand denoted by p_{Dnt} and q_{Dnt} , plus energy storage, with charging power denoted by p_{CHnt} , discharging power denoted by p_{DCHnt} , and energy buffer denoted by e_{nt} . In addition, consider that up to A additional (static or mobile) generation and storage units can be connected to the network as needed. The presence of additional distributed energy resources at bus $n \in N$ is determined by the binary variables α_{nt} , set to 1 if present and 0 if absent.

5.2 Constraints

The optimization problem is constrained by the operating constraints of the network, given by power flow equations and the number of additional distributed energy resources that can be connected to the network. Here the linearised power flow equations adopted by [19] are used in the formulation.

Constraints (1) and (2) limit the active and reactive load demand supplied at a bus to their corresponding projected values over time:

$$\underline{P}_{Dnt} \leq p_{Dnt} \leq \overline{P}_{Dnt} \quad (1)$$

$$\underline{Q}_{Dnt} \leq q_{Dnt} \leq \overline{Q}_{Dnt} \quad (2)$$

Likewise, constraints (3) and (4) limit the active and reactive power supplied at a bus to their corresponding lower and upper limits over time:

$$\underline{P}_{Gnt} \leq p_{Gnt} \leq \overline{P}_{Gnt} \quad (3)$$

$$\underline{Q}_{Gnt} \leq q_{Gnt} \leq \overline{Q}_{Gnt} \quad (4)$$

Storage units exchange power with the network by charging or discharging over time, subject to constraints (5)–(8). Constraints (5) and (6) limit the charging and discharging power at bus n to its maximum values, whereas constraints (7) and (8) limit the energy buffer over time:

$$0 \leq p_{CHnt} \leq \overline{P}_{CHn} \quad (5)$$

$$0 \leq p_{DCHnt} \leq \overline{P}_{DCHn} \quad (6)$$

$$\underline{E}_n \leq e_{nt} \leq \overline{E}_n \quad (7)$$

$$e_{nt+1} = e_{nt} + \Delta t \left(p_{CHnt} \eta_{CHn} - \frac{p_{DCHnt}}{\eta_{DCHn}} \right) \quad (8)$$

In the presence of additional static or mobile generation and storage units at bus n, (3)–(7) should be replaced with (9)–(13) to account for an increase in their corresponding lower and upper limits:

$$\underline{P}_{Gnt} + \alpha_{nt} \underline{P}_{AGnt} \leq p_{Gnt} \leq \overline{P}_{Gnt} + \alpha_{nt} \overline{P}_{AGnt} \quad (9)$$

$$\underline{Q}_{Gnt} + \alpha_{nt} \underline{Q}_{AGnt} \leq q_{Gnt} \leq \overline{Q}_{Gnt} + \alpha_{nt} \overline{Q}_{AGnt} \quad (10)$$

$$0 \leq p_{CHnt} \leq \overline{P}_{CHn} + \alpha_{nt} \overline{P}_{ACHn} \quad (11)$$

$$0 \leq p_{DCHnt} \leq \overline{P}_{DCHn} + \alpha_{nt} \overline{P}_{ADCHn} \quad (12)$$

$$\underline{E}_n + \alpha_{nt} \underline{E}_{An} \leq e_{nt} \leq \overline{E}_n + \alpha_{nt} \overline{E}_{An} \quad (13)$$

Power flow constraints are given by (14)–(21), with (14)–(17) limiting active and reactive power flows at branch e to the line ratings, (18)–(19) enforcing power balance at bus n , (20) defining voltage drops between the origin and destination buses of branch e , and (21) limiting voltage magnitude at bus n to its lower and upper admissible values:

$$-\overline{S}_{et} \leq p_{et} \leq \overline{S}_{et} \quad (14)$$

$$-\overline{S}_{et} \leq q_{et} \leq \overline{S}_{et} \quad (15)$$

$$-\sqrt{2\overline{S}_{et}} \leq p_{et} + q_{et} \leq \sqrt{2\overline{S}_{et}} \quad (16)$$

$$-\sqrt{2\overline{S}_{et}} \leq p_{et} - q_{et} \leq \sqrt{2\overline{S}_{et}} \quad (17)$$

$$p_{Gnt} - p_{Dnt} + p_{DCHnt} - p_{CHnt} = \sum_{e \in E | OR(e)=n} p_{et} - \sum_{e \in E | DE(e)=n} p_{et} \quad (18)$$

$$q_{Gnt} - q_{Dnt} = \sum_{e \in E | OR(e)=n} q_{et} - \sum_{e \in E | DE(e)=n} q_{et} \quad (19)$$

$$v_{DE(e)t} - v_{OR(e)t} = \frac{r_e p_{et} + x_e q_{et}}{v_0} \quad (20)$$

$$\underline{V}_n \leq v_{nt} \leq \overline{V}_n \quad (21)$$

Constraints on the number of additional generation and storage units that can be connected to the network are given by A in (22):

$$\sum_{n \in N} \alpha_{nt} \leq A \quad (22)$$

5.3 Objective Function

The objective function aims at minimising performance degradation in the provision of electricity by the DSO. Here the ENS is chosen as a performance indicator, as it accounts for the amount of load energy unserved at all network buses during the evaluation horizon. Note that other relevant performance indicators (e.g., customer interruptions, accumulated costs) can be used without loss of generality. The problem formulation adopts quadratic terms in order to penalise higher deviations between projected and actual load demand values over time:

$$\min \sum_{t \in T} \sum_{n \in N} (\bar{P}_{Dnt} - p_{Dnt})^2 \quad (23)$$

Subject to constraints (1)–(22).

6 Results and Discussions

In this section, the methodology is demonstrated on a realistic LV distribution network in the United Kingdom. This choice is made to illustrate the challenges posed by severe weather conditions and opportunities brought by new energy technologies (under certain operating conditions) at lower distribution voltage levels. The next paragraphs describe the test case and results obtained for two different scenarios.

6.1 Test Case

The real-world three-phase unbalanced LV network used in this section is mapped in Fig. 3. It has 330 single-phase residential loads connected to a three-phase 125 kVA Dyn11 transformer through 329 power distribution lines in

radial configuration with nearly 7 km total length and 125 kVA ratings. More details about the network are provided by [20, 21]. Time-varying generation and load demand profiles were obtained from solar energy outputs provided by [22] and load demand values provided by [23] considering a neighbourhood in Bristol, United Kingdom. The voltage magnitude at the substation (slack) bus $n = 1$ is set to $v_{1t} = 1.02$ p.u., whereas admissible values are within the range between $\underline{V}_n = 0.94$ p.u. and $\overline{V}_n = 1.06$ p.u. at the other buses.

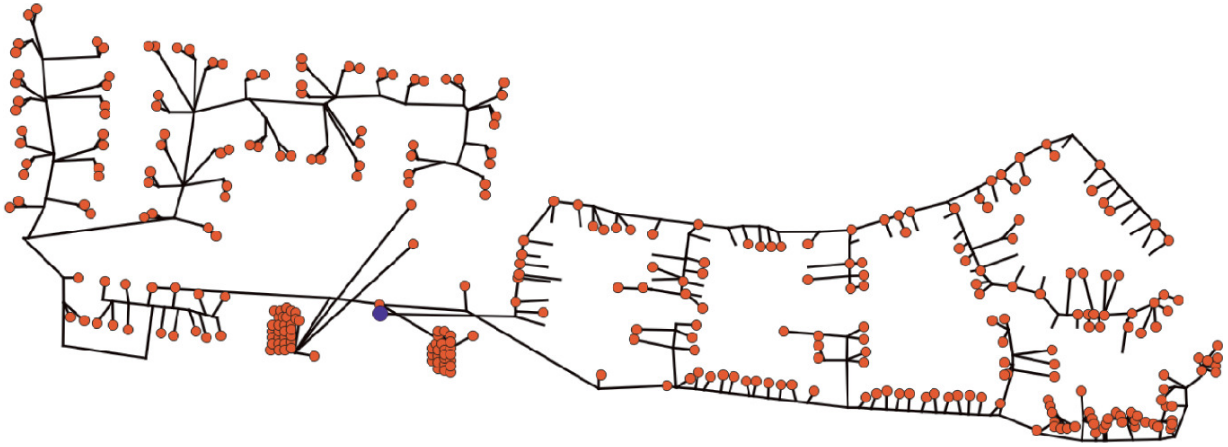


Fig. 3 Schematic representation of the power distribution network showing the distribution lines (black lines), substation (purple circle), and 330 load buses (red circles)

The analysis is conducted with hourly generation and demand profiles obtained in July 2019 over a 3-day horizon representing the onset of a heatwave scenario. It is assumed that the current-carrying capability of the transformer and lines is reduced up to 50% for safety reasons. In this situation, the methodology is implemented to determine the optimal locations in which sets of solar photovoltaic panels plus battery storage units should be installed to provide back-up support to the distribution substation—minimising the ENS values over time. Thus, it is assumed that the network might have up to $A = 66$ distributed generation units (i.e., sets of solar photovoltaic

panels plus battery storage units), which is equivalent to 20% of households connected to the network.

The solar photovoltaic panels are rated at $\overline{P}_{Gn} = 2$ kWp and the battery storage specifications are $\overline{P}_{CHn} = \overline{P}_{DCHn} = 3$ kW, $\eta_{CHn} = \eta_{DCHn} = 0.98$, $\overline{E}_n = 29.25$ kWh, $\underline{E}_n = 0.75$ kWh. It is assumed that sets of solar photovoltaic panels plus battery storage units can only be connected to the same bus and phase as loads and that each load can have up to one of these sets, according to typical installation practices adopted by households.

To account for changes in future operating conditions, the heatwave scenario under consideration is evaluated over a 5-year horizon under the assumption that there is a 5% load demand growth every year (i.e., $\overline{P}_{Dnt}$ at a given bus and time interval for year 5 is equal to $1.05^4 \overline{P}_{Dnt}$ at the same bus and corresponding time interval for year 1). To illustrate the difference between different year periods, ENS values and optimal locations for distributed energy resources are reported in separate for each year. The total load energy over this 3-day period is equivalent to 10,145 kWh for the first (reference) year.

Two different situations are evaluated in the next section: (1) up to $A = 66$ DERs connected to the same bus and phase as some loads in the network (Sect. 6.2.1) and (2) up to $A = 66$ DERs connected to the same bus and phase as some loads in the network plus flexible shiftable loads corresponding to up to 20% of the load demand (Sect. 6.2.2).

The optimisation problem is implemented in Python 3.9 and solved with Gurobi 10.0.0. Results are shown in the next section.

6.2 Results

6.2.1 Distributed Energy Resources

This section presents the results obtained for the first test case described in Sect. 6.1 considering different year periods with and without the presence of DERs. Table 3 lists the total ENS values for the heatwave scenario previously described when it occurs in different year periods. In turn, Fig. 4 shows the optimal positioning of DERs obtained for different year periods.

Table 3 ENS values obtained for the heatwave scenario when it occurs in different year periods calculated with and without the presence of DERs

Year		1	2	3	4	5
Total ENS value (in kWh)	With DERs	1.466	1.692	1.960	2.226	2.582
	Without DERs	1.179	1.470	1.815	2.219	2.681

For an easy reading, decimal points were rounded to their nearest integer value

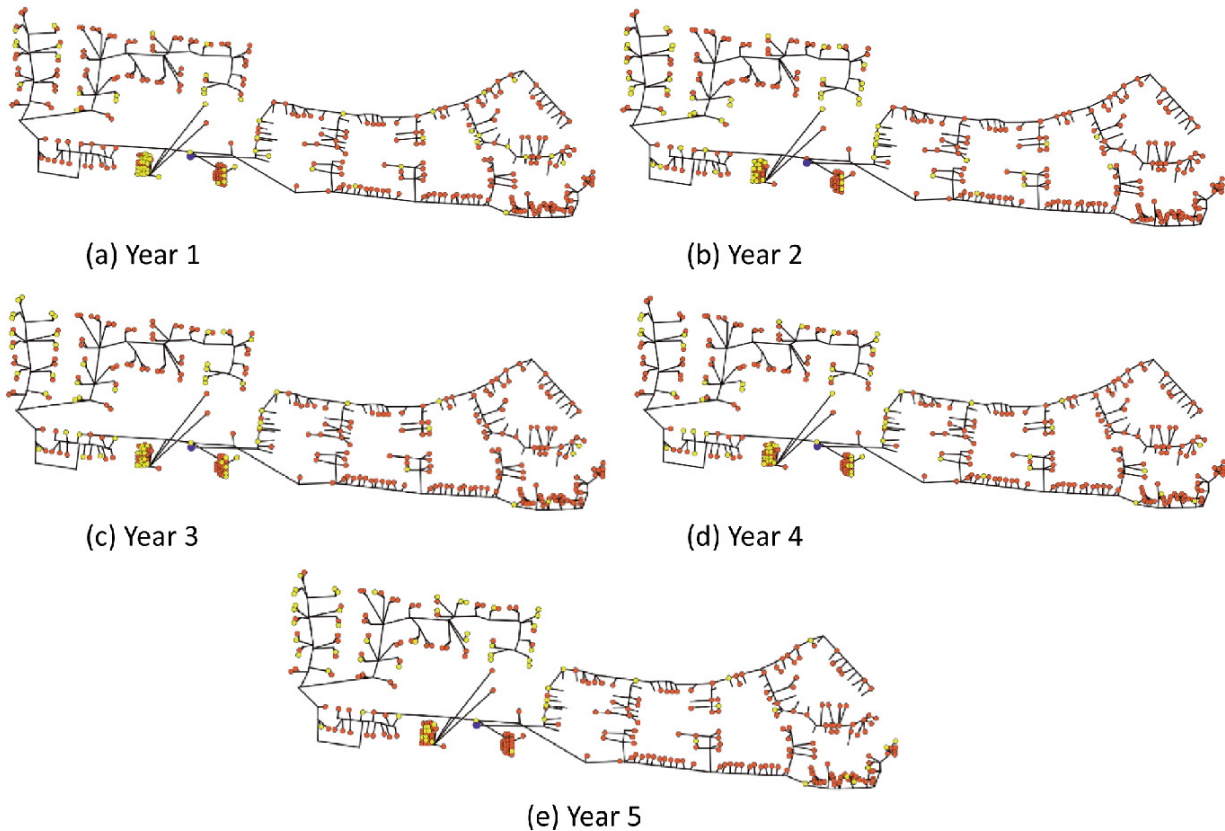


Fig. 4 Schematic representation of the power distribution network showing the distribution lines (black lines), substation (purple circle), and load buses without distributed energy resources (red circles) and selected as optimal locations for installation of distributed energy resources (yellow circles) for year periods 1 (a) to 5 (e), first test case

Note that the ENS values listed in Table 3 increase over time as expected regardless of the presence of DERs, as the load demand increases without any network upgrades in this case study. However, the benefits provided by contributions from DERs to decrease ENS values are only evident in the final year period. In this situation, the network capacity constraints significantly overcome the substation's ability to supply its connected customers, deviations between projected and actual load demand values are higher, and DERs are helpful to provide local supply within acceptable operating limits. Also note that the quadratic objective function adopted within this formulation penalises higher deviations more heavily than smaller deviations.

In addition, note some differences in the optimal locations of DERs for different year periods. This can be attributed to load demand increases along with tighter network constraints as defined by power flows, which heterogeneously affect the network operating conditions. This can also be attributed to the solar irradiance profiles, which could have yielded to different results during a different study period (i.e., with a different time duration and/or reference dates). Likewise, the usage of different types of DERs (e.g., wind turbines, standalone solar PV panels, plug-and-play mobile energy storage units) could yield to very different results.

6.2.2 Load Demand Flexibility Options

This section presents the results obtained for the second test case described in Sect. 6.1 considering different year periods with the presence of up to $A = 66$ DERs and with and without the presence of shiftable loads. Table 4 lists

the total ENS values for the heatwave scenario previously described when it occurs in different year periods. In turn, Fig. 5 shows the optimal positioning of DERs obtained for year period 5 when up to 20% of the load demand is shiftable.

Table 4 ENS values obtained for the heatwave scenario when it occurs in different year periods calculated with and without the presence of shiftable loads when DERs are present

Year		1	2	3	4	5
Total ENS value (in kWh)	With load shift	347	468	622	807	1.340
	Without load shift	1.466	1.692	1.960	2.226	2.582

For an easy reading, decimal points were rounded to their nearest integer value

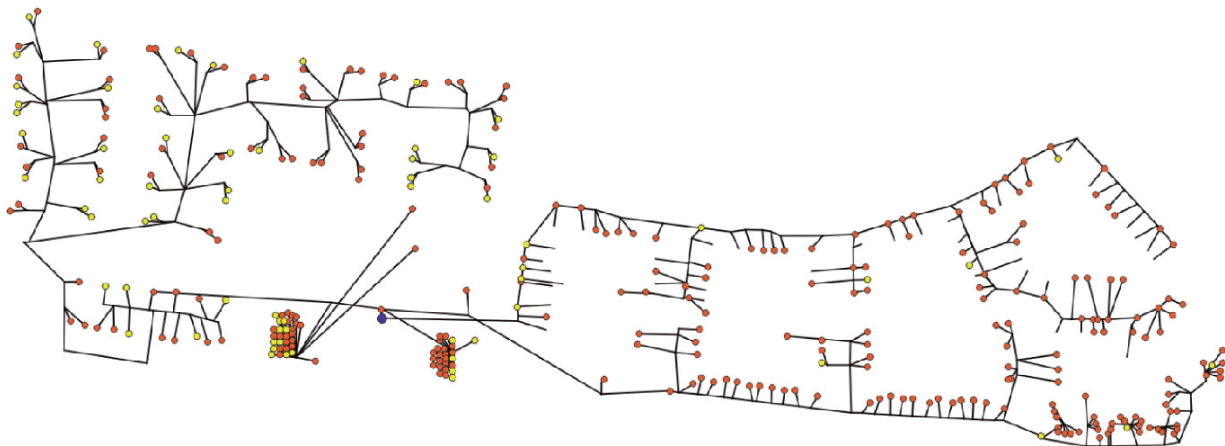


Fig. 5 Schematic representation of the power distribution network showing the distribution lines (black lines), substation (purple circle), and load buses without distributed energy resources (red circles) and selected as optimal locations for installation of distributed energy resources (yellow circles) for year period 5, second test case

Note the influence of shiftable loads on the ENS values shown in Table 4 over time: ENS values calculated with the presence of shiftable loads are nearly a quarter of ENS values calculated without them in year period 1; and nearly half the ENS values calculated without them in year period 5. This is an expected result, as the contribution from

shiftable loads for demand reduction is not sufficient to compensate for the reduction in available network capacity over time. The load demand increases without any network upgrades in this case study.

It is noteworthy that the role of DERs to alleviate network congestion is only relevant in year period 5. In year periods 1–4, the usage of DERs does not contribute for the optimal solution computed with (23) and is excluded from the calculated results. Note that there are some differences in the optimal locations of DERs obtained for year period 5 without and with the presence of shiftable loads in Figs. 4e and 5. This can be attributed to the differences in the equivalent load demand along with network constraints as defined by power flows, which affect the network operating conditions in different ways.

6.3 Discussions

The results previously obtained may vary considerably for different year periods as a function of the load demand growth and system effects. These factors affect the results calculated with (23) directly. Consequently, the optimal set of DER locations contains the load buses affected by the heatwave scenario which best mitigate violation of operating constraints given by (1)–(22). This can be noticed in Figs. 4a–e and 5, as the optimal DER locations do not change significantly with the experimental settings.

Differences in load demand values imply that some loads can be more troublesome than others to maintain the network operation within acceptable limits, for being heavier and connected to parts of the network under higher stress (i.e., tighter power flow constraints, reduced even further during the heatwave). To this extent, severe heatwave episodes are more likely to justify the decision of deploying flexibility options at distribution voltage levels, as the longer the stress duration, the larger the values of (23). This is particularly relevant for decisions concerning

parts of the network with relatively small amounts of load demand but tight spare capacity.

The results summarized in Tables 3 and 4 indicate that the adoption of flexibility options may contribute to reduce the ENS values during heatwaves. However, benefits provided by DERs are only evident when network congestion is significant (that is, when capacity constraints are considerably tight), as these technologies also alter power flows and operating constraints. This can be noticed by comparing the “with DERs” and “without DERs” rows in Table 3. Thus, comparing the “as is” and “proposed” benchmarking scenarios is recommended to identify the resilience enhancements that should be prioritized where and when. Also note that the benefits provided by temporary demand reduction through load shifting are more evident than the benefits provided by DERs in this test case, as shown in Table 4. However, this strategy may be impractical when critical loads and vulnerable customers are connected to the network and there are no alternative back-up supply sources.

The overlap among selected locations for DERs in Figs. 4 and 5 obtained with the proposed methodology also suggests that some of the highest impacts are observed in the same parts of the network, depending on the accumulated ENS values over time. Again, the technical specifications and system effects play an important role in the performance assessment. Conversely, adopting a different decision criterion in (23) could lead to a different choice of DER locations, with some variations between different year periods and resilience enhancement measures.

From a system perspective, investing in resilience enhancements is advantageous when the benefits outweigh the costs or risks. This motivates the adoption of optimal resilience planning and operational resilience assessment and enhancement decisions. Overall, the results indicate

that resilience enhancement measures are advantageous to reduce inconveniences associated with load energy unserved, especially in a mid- to long-term horizon and considering future climate scenarios.

6.4 Recommendations for Utilities

Table 5 summarizes key recommendations for utilities to address existing resilience gaps and mitigate risks associated with severe weather events in a changing climate in active distribution networks. Overall, planning measures implementable during the anticipatory stage require high investment cost several years in advance in the pre-disaster phase, whereas operational measures implementable during the response and recovery stages imply high operational costs in the disaster and post-disaster phases. For more details, refer to [7, 14, 24].

Table 5 Key recommendations for energy utilities to mitigate risks associated with severe weather events in a changing climate for active distribution networks

Stage	Risk mitigation actions
Anticipate	• Improve assessment of risks associated with severe weather events and climate change at planning stage for risk-informed investment decisions • Devise resilience planning strategies that take into account energy transition pathways and future energy scenarios (e.g., load growth, increasing renewable energy penetration, smart grid technologies, generation decommissioning, ageing network components) • Combined cost-benefit analysis of hardening strategies and capacity procurement and expansion for decisions concerning network upgrades • Improve assessment of risks associated with interdependencies for context-aware investment decisions at regional level • Revise appropriateness of incentive schemes and investment targets defined by regulations for network resilience • Develop decision support tools to evaluate different aspects of resilience

Stage	Risk mitigation actions
	• Develop standards on power grid infrastructure resilience to set public and government expectations and industry targets and guide planning and investment decisions • Establish working groups for exchange of knowledge, models, and data about risks associated with severe weather events in a changing climate (at national and international levels) • Extensively training of operation teams on the handling of severe weather events and their consequences on the power system
Respond	• Improve early warning systems to quickly identify faults and extent of network damage and power outages, taking advantage of AMI, PMUs, IoT, among other sources of data • Pre-disaster pre-positioning of mobile energy resources and repair and restoration crews at strategic locations (to reduce performance degradation and/or provide corrective actions as needed) • Improve emergency response plans through combined actions (e.g., network reconfiguration, contingency reserves, emergency generators, energy storage options) • Make flexibility options (e.g., energy storage, demand response) readily available to compensate for infrastructure damage and service degradation • Make use of spatiotemporal forecasting tools to improve effectiveness of implementation of emergency plans • Enable intentional controlled island mode operation during severe weather events to prevent cascading failures in unaffected parts of the network • Improve knowledge of disturbance development and propagation scenarios to prevent cascading failures • Improve resilience and increase availability of communication channels for the handling of fault incidents • Review severe weather escalation plans to ensure that all relevant factors which can influence scale of impacts are taken into account • Coordinate efforts with other DSOs and critical infrastructure and service providers for a timely response to severe weather events • Define clear roles and responsibilities of different stakeholders during severe weather events
Recover	• Deploy DERs in combination with black-start units for a quicker distributed re-energization of affected parts of the network

Stage	Risk mitigation actions
	• Increase modularity of network components for a quicker power grid infrastructure recovery • Prioritize restoration of critical loads, including critical infrastructure and services and vulnerable customers, to reduce negative impacts of power outages on the economy and society • Conduct risk and contingency assessments at community level and prioritize recovery of groups at high risk of disruption • Coordinate efforts with other energy utilities and critical infrastructure and service providers for a faster recovery process • Learn from past events and adapt anticipation, response, and recovery plans to enhance power grid resilience to severe weather events at different conceptual stages • Collect data from past events to improve anticipation, response, and recovery plans

Left column lists conceptual stages of resilience, whereas right column lists corresponding risk mitigation actions for active distribution networks

7 Conclusions

This section describes the main findings of this chapter and future perspectives on enhancing resilience of active distribution networks to severe weather events now and in the future.

7.1 Main Findings

Decarbonization, climate change, and digitalization are bringing significant changes to electrical power systems worldwide. In this ever-changing scenario, power distribution networks are evolving from passive to active, and becoming increasingly vulnerable to severe weather events, thanks to an increasing uptake of low carbon distributed energy resources and electrification of different economy sectors. To address this challenge, this chapter described how active power distribution networks can take

advantage of distinct strategies and enabling technologies to maintain or improve their resilience to severe weather, considering different implementation timescales. These aspects were embedded in an optimization problem formulation aimed at improving the network operating performance under severe weather conditions, taking advantage of additional distributed energy resources for resilience enhancements over different planning and operational timescales. Simulation results derived from implementation in a realistic distribution network in the United Kingdom show that these technologies are able to provide resilience enhancement benefits in different ways. These results are very encouraging for the value of these technologies under exceptional circumstances, as well as the opportunities brought by new technologies to enhance resilience of active distribution networks.

7.2 Future Perspectives

This section contains considerations about climate change mitigation and adaptation efforts, as well as new technologies, multi-energy systems approaches, and regulatory frameworks needed for a resilient net zero future.

7.2.1 Climate Change Mitigation and Adaptation in Active Distribution Networks

Efforts to promote climate change mitigation (through decarbonization) and adaptation (through resilience enhancements) in energy systems must be combined and intensified in the next few years. To achieve this, planning and operational measures should be selected and implemented to simultaneously achieve decarbonization and resilience benefits while considering operating constraints and performance satisfaction. This is extremely important so that energy networks can successfully

accommodate an increasing electrification of different economy sectors. For this to be possible, however, improvements in energy and climate data, models, and scenarios are highly needed at different regional levels so that relevant risks can be correctly identified and mitigated. By incorporating climate change mitigation and adaptation measures in line with projected changes in electricity supply, demand, and capacity requirements and accurate data, models, and scenarios, DSOs will achieve a resilient net zero energy future.

7.2.2 New Smart Grid Technologies for Active Distribution Networks

The presence of ICT in distribution networks will become much more widespread in the next few years, along with an increasing penetration of DERs and flexibility options. As a result, passive distribution networks will become active and active distribution networks will become even more active. This paradigm shift will bring challenges and opportunities for DSOs, requiring distributed control and multi-agent strategies for the coordination of different parts of the network and conflicting objectives. Requirements for data collection, processing, storage, and latency are also expected to increase as decisions become more dependent on ICT.

7.2.3 Data Analytics and Artificial Intelligence

The more widespread the presence of ICT in distribution networks, the larger the amounts of data generated by the active distribution networks. These vast amounts of data will increase the requirements and require innovative approaches for data analytics in active distribution networks. Usage of data analytics in combination with artificial intelligence is expected to significantly improve understanding of the network and its different components

now and in the future. It will also be useful to retrieve pieces of information that cannot be easily found in the datasets, such as small disturbances and complex features of certain components or parts of the network. By improving understanding of the network and its components, data analytics and artificial intelligence methods will also contribute to improve resilience assessment and enhancements in active distribution networks and beyond.

7.2.4 Contributions from Multi-Energy Systems and Energy Systems Integration

Contributions from MES are expected to dramatically increase in the next few years. By complementing and providing an alternative to electrification, MES approaches will be more resilient to external events, including different severe weather event categories, than individual energy carriers. The resulting MES will have increased robustness, resourcefulness, and additional routes for a quick recovery process, leveraging options that would not be available otherwise.

7.2.5 New Regulatory Frameworks

The increasing transformation of distribution networks from passive to active will require important changes in standards and regulations to facilitate implementation of pertinent changes in design and operational practices. These changes are envisaged to facilitate widespread adoption of new smart grid technologies along with DERs and flexibility resources, helping pave the way for a resilient net zero future. These changes will also contribute to enforce resilient net zero principles throughout the design and operation phases of active distribution networks.

References

1. OECD (2012) ICT applications for the smart grid: opportunities and policy implications. In: OECD digital economy papers, No. 190. OECD Publishing, Paris. <https://doi.org/10.1787/5k9h2q8v9bln-en>
2. Zambroni De Souza AC, Venkatesh B (eds) (2022) Planning and operation of active distribution networks: technical, social and environmental aspects. In: Lecture notes in electrical engineering, vol 826. Springer, New York. <https://doi.org/10.1007/978-3-030-90812-6>
3. Xu L et al (2024) Resilience of renewable power systems under climate risks. Nat Rev Electr Eng 1:53–66. <https://doi.org/10.1038/s44287-023-00003-8>
[Crossref]
4. Sarantakos I et al (2022) (2022) A robust mixed-integer convex model for optimal scheduling of integrated energy storage: soft open point devices. IEEE Trans Smart Grid 13(5):4072–4087. <https://doi.org/10.1109/TSG.2022.3145709>
[Crossref]
5. Taylor PC et al (2022) An interdisciplinary research perspective on the future of multi-vector energy networks. Int J Electr Power Energy Syst 135:107492. <https://doi.org/10.1016/j.ijepes.2021.107492>
[Crossref]
6. CIGRE working group C4.47 (2019) Defining power system resilience. <https://www.cigre.org/article//defining-power-system-resilience>
7. Stankovic AM et al (2022) Methods for analysis and quantification of power system resilience. IEEE Trans Power Syst 14(8):1–14. <https://doi.org/10.1109/tpwrs.2022.3212688>
[Crossref]
8. International Energy Agency (2015) Making the energy sector more resilient to climate change. IEA, Paris. <https://www.iea.org/reports/making-the-energy-sector-more-resilient-to-climate-change>
9. Carrington NK, Dobson I, Wang Z (2021) Extracting resilience metrics from distribution utility data using outage and restore process statistics. IEEE Trans Power Syst 36(6):5814–5823. <https://doi.org/10.1109/TPWRS.2021.3074898>
[Crossref]
10. Braun M, Hachmann C, Haack J (2020) Blackouts, restoration, and islanding: a system resilience perspective. IEEE Power Energy Magazine 18(4):54–63. <https://doi.org/10.1109/MPE.2020.2986659>

- [Crossref]
11. Souto L et al (2022) Power system resilience to floods: modeling, impact assessment, and mid-term mitigation strategies. *Int J Electr Power Energy Syst* 135:107545. <https://doi.org/10.1016/j.ijepes.2021.107545> [Crossref]
 12. Souto L, Taylor PC, Pregnotato M (2022) Routing and dispatching of mobile storage units for a resilient response to severe weather events in low voltage smart grids. In: *Proceedings of the 2022 IEEE PES innovative smart grid technologies conference Europe (ISGT-Europe)*, Novi Sad, Serbia, pp 1–5. <https://doi.org/10.1109/ISGT-Europe54678.2022.9960695>
 13. Zhao T, Parisio A, Milanović JV (2020) Distributed control of battery energy storage systems for improved frequency regulation. *IEEE Trans Power Syst* 35(5):3729–3738. <https://doi.org/10.1109/TPWRS.2020.2974026> [Crossref]
 14. National Grid Electricity Transmission (2021) Climate change adaptation report. <https://www.nationalgrid.com/electricity-transmission/document/143211/download>
 15. IPCC (2014) Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. In: Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds) *Contribution of Working Group II to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge, p 1132
 16. Yates D et al (2014) Stormy weather: assessing climate change hazards to electric power infrastructure—a sandy case study. *IEEE Power Energy Magazine* 12(5):66–75. <https://doi.org/10.1109/MPE.2014.2331901> [Crossref]
 17. National Infrastructure Commission (2023) The second national infrastructure assessment. <https://nic.org.uk/app/uploads/Final-NIA-2-Full-Document.pdf>
 18. Souto L (2023) Optimal siting of distributed generators in renewable-based community energy system for self-sufficient operation during prolonged outages. *IET Conf Proceed* 32:184–187. <https://doi.org/10.1049/icp.2023.3237> [Crossref]
 19. Yao S, Wang P, Liu X, Zhang H, Zhao T (2020) Rolling optimization of mobile energy storage fleets for resilient service restoration. *IEEE Trans Smart Grid* 11(2):1030–1043 [Crossref]

20. Navarro-Espinosa A, Ochoa L (2015) Dissemination document “low voltage networks models and low carbon technology profiles”, pp 1-27
21. Deakin M, Greenwood D, Walker S et al (2021) Hybrid European MV-LV network models for smart distribution network modelling. In: Proceedings of the 2021 IEEE Madrid PowerTech, Madrid, Spain, pp 1-6
22. Pfenninger S, Staffell I (2016) Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 114:1251-1265
[[Crossref](#)]
23. Barton J, Thomson M, Sandwell P et al (2020) A domestic demand model for India. In: Singh S, Ramadesigan V (eds) Advances in energy research. Springer, Singapore, pp 743-753
24. Ofgem (2022) Storm Arwen technical review of DNO response. <https://www.ofgem.gov.uk/sites/default/files/2022-06/GHD%20-%20Storm%20Arwen%20Review%20Main%20Report.pdf>

Peak Load Reduction and Resilience Benefits in Critical Microgrids

Enrique Rosales-Asensio¹, Daniel Icaza², Noemi González-Cobos³ and David Borge-Diez⁴ 

- (1) Department of Electrical Engineering, University of Las Palmas de Gran Canaria, Campus de Tafira S/n, 35017 Las Palmas de Gran Canaria, Canary Islands, Spain
- (2) Catholic University of Cuenca, Av. de Las Américas y Humboldt, Cuenca, Ecuador
- (3) Instituto Tecnológico de La Energía (ITE), 46980 Paterna, Valencia, Spain
- (4) Departament of Electrical, Systems and Automation Engineering, University of León, Campus de Vegazana, S/N, 24071 León, Spain

 **David Borge-Diez**
Email: dbord@unileon.es

Abstract

Microgrids configured using a specific control system to provide correct power quality for local loads that can be either connected or disconnected from the grid, operating grid-connected or islanded mode can be designed to

improve the resilience of critical energy systems. In case of grid failure, an energy storage combined with one or several local generators can provide backup power and considering both conventional and renewable energy systems, this research presents an operational resilience analysis for critical facilities, in this case a hospital. The proposed methodology allows studying the possibility to maintain the energy supply and evaluating resilience benefits of a microgrid integrated in critical facilities when power outages occur. Optimization of the dispatch and heating and cooling strategies is presented and analyzed and a case study characterizing an electric polygeneration microgrid feeding critical loads is presented. Results show the benefits and the increased energy resilience resulting from the use of solar PV, electrochemical batteries, combined heat and power, TES water tanks and absorption chillers and proposes a design and optimization scheme that can be applied for similar facilities and extensive to any critical loads. Economic results prove the economic benefits resulting from the use of an optimal resilient microgrid. In particular, it is found that, in the event of an outage, the positive monetary effects last longer than the duration of the outage.

Keywords Peak load reduction – Resilience benefits – Resilience analysis – Dispatch optimization – Critical microgrids

Nomenclatures

CHP Combined heat and power

MMBTU Million British thermal units

NPV Net present value

PV Photovoltaic

TES Thermal energy storage

1 Introduction

The issue of resilience has recently become of great importance for energy systems [1]. Despite the fact that more people than ever have access to electricity [2] (about 90% of the world's population [3]), severe power outages are now occurring that threaten millions of people and have caused multi-billion dollar damage to power systems located in countries with high-income economies [4]. A growth in electricity demand [5], vandalism [6], and reduced availability of fresh water, together with an increase in the number or intensity of extreme climate issues [7] can restrict power transmission capacity and eventually lead to an electrical blackout [8]. In this sense, and following the definition provided by Wing and Rose [9], a resilient system would be one that, recognizing the likelihood of long-duration power outages over a wide area, prepares for such power outages, minimizes their impact when they occur, is able to restore service quickly, and draws lessons from the experience to improve its performance in the future [9]. Hitherto, stand-alone diesel generators have been the only economically viable option for providing near-instantaneous backup power [10]. However, with the increasing focus by local and national governments on low-carbon and resilient energy systems, other technologies may better meet these requirements [10].

A microgrid is defined by a specific control system that ensures power quality for local loads [11, 12] that can be connected or disconnected from the grid and operate in either grid-connected or islanded mode [13, 14]. The average U.S. household experiences 1.3 power outages per year, and the average duration of each power outage is about four hours [15]. In advanced economy power systems, the time during which a conventional generator is

actually generating backup power would predictably be similar to that amount of time [10]. While it is true that, for maintenance purposes, a conventional backup generator should be in operation a minimum of 26 h per year [16], such generators should not operate more than 200 h per year at an average load of 80% of their rated peak power [17]. This limited number of hours in which a conventional backup system is actually in operation differs substantially from the number of hours in operation that would be achieved with renewable energy resources (in the case of solar PV, the capacity factor is usually between 25 and 30% of annual demand [18, 19]). In case of grid failure, an energy storage combined with one or several local generators can provide backup power [20].

In case an outage occurs, microgrids can play an important role in ensuring a continuous and cost-effective power supply [21]. A key aspect of microgrids is the fact that, in the event of a blackout in the conventional power grid, disconnection from the grid can be carried out in order to maintain, at a minimum, the customer's critical loads [22, 23]. The integration of distributed resources and microgrids into distribution systems and microgrids offers a great opportunity to develop efficient restoration methodologies [24, 25]. On the other hand, electric power generation from distributed resources is progressively becoming more competitive compared to conventional generators [26]. Microgrids can reduce the cost of outages for facility owners and the communities that depend on them, including improving the economics and energy resilience of local energy communities [27]. Because of this, the power sector has turned to microgrids to provide critical resilience in the event of local and regional power outages [28]. As discussed above, controlled microgrids can provide sustainable supply at reduced cost [29] and be the answer to ensure that local energy communities have access to reliable electricity in times of emergency [30].

Failures in critical infrastructures can cause great damage to society [31]. Because virtually all critical infrastructures depend on the power grid [32], protection of critical electrical infrastructures is imperative for national security [33]. Health care institutions are facilities where the costs of load loss can be substantially higher than the costs of backup power [34, 35]. This is because monetary effects are likely to occur for a duration longer than the duration of the power outage [36]. Despite this, it may be difficult to achieve sufficient savings and avoided costs to cover the entire microgrid system, so, in order to implement the entire project, it may be necessary to leverage these avoided costs in combination with appropriate funds [37].

In the scientific literature, it is possible to find works that provide new statistical methodologies to calculate the impact of reliability and variability of distributed energy on the performance of a microgrid [38]; other works that present a quantitative methodology to compare the reliability of a microgrid architecture based on centralized emergency diesel generators is [39]; other works providing a novel method for incorporating the value of resilience provided by PV panels and battery energy storage into a techno-economic optimization model [40]; and still other works empirically deriving uncertainty ranges in the optimal costs of solar PV and storage [41]. However, very little work has been done in the scientific literature regarding the optimization of microgrid dispatch, heating and cooling strategies. In this regard, this research article will study peak load reduction and resilience benefits using solar PV, electrochemical batteries, cogeneration, TES water tanks, and absorption chillers.

From a deep survey of grey literature and updated literature related to the topic addressed here, it was possible to find that—even though there are plenty deal of different approaches—this chapter undoubtedly contributes

to the pool of existing knowledge by giving a dispatch, heating thermal, and cooling thermal strategies optimization to a microgrid (to our knowledge, so far not addressed in the scientific literature). By performing this thorough literature review, we ensure the originality of the idea and method here presented. From this line of analysis, a much clearer insight of electricity dispatch, and heating thermal and cooling thermal strategies impact on the feasibility and resilience of microgrids with critical loads is gained (so far not explicitly shown to our knowledge in any scientific paper). Furthermore, the proposed method here presented improves analysis in the sense that a systematic and easy approach manages to make comparisons among a number of microgrids with critical loads regardless of their sizes and locations.

The research presented here optimizes a microgrid system with critical loads that, connected to the general power grid, provides backup power during power outages. In order to carry out this optimization, the life cycle cost of the project will be minimized. To make up for the insufficiency of the scientific outcomes in this field, the research presented here describes the power dispatch strategy for a microgrid with critical loads, maximizing the benefits provided by distributed generators to the energy resilience of the aforementioned microgrid. The scope of the research presented here also includes the simulation of power outages. Based on the above, the contribution of the research presented here would be threefold, namely, (a) evaluation of the economic viability of a microgrid with critical loads connected to the general power grid using solar PV, electrochemical batteries, cogeneration, TES water tanks, and absorption chillers; (b) optimization of the dispatch, heating and cooling strategies of a microgrid; (c) strategies for improving energy resilience through a comparison between the current situation and another scenario that evaluates the proposed microgrid.

Following the definition provided by Linkov et al. [42], a resilient system would be defined through “its ability to perform four functions with respect to adverse events, namely, (i) planning and preparation, (ii) absorption, (iii) recovery, and (iv) adaptation”. The term “energy resilience” refers to the ability to avoid, prepare for, minimize, adapt to, and recover from planned and unplanned energy disruptions in order to ensure the necessary degree of availability and reliability of electric power [43]. Infrastructure resilience refers to the physical strength of a power system to mitigate the part of the system that is damaged, collapsed, or generally ceases to function [44]. Following the definition provided by Panteli et al., operational resilience, as the name implies, “refers to the characteristics that would secure operational strength for a power system, e.g., the ability to ensure the uninterrupted supply to customers or generation capacity availability in the face of a disaster” [44]. The scope of the research presented here focuses on the latter, operational resilience. While the planning and adaptation stages are important, the research presented here focuses on absorption and, to some extent, resilience. This is because the scope of the research presented here is the study of the ability to maintain, whenever possible, the energy supply. It should be noted that the research presented here is especially devised to evaluate resilience benefits of a microgrid in which power outages occur.

In this first section, the possibility of optimizing the dispatch, heating and cooling strategies of a microgrid with critical loads has been briefly analyzed; in the second section, the method used to carry out the research is presented; in the third section, case studies for an electric microgrid are presented. This section will discuss the possibility of reducing peak loads in such a microgrid as well as the potential benefits in terms of energy resilience resulting from the use of solar PV, electrochemical

batteries, cogeneration, TES water tanks and absorption chillers; finally, the fourth section will present the conclusions obtained from the research presented here.

2 Materials and Methods

The general approach to conduct the investigation is detailed in this section. Figure 1 presented below indicates the procedure to be followed to carry out the research presented in this chapter using Reopt Lite, which is a software developed by the National Renewable Energy Laboratory that allows analyze energy system of different nature.

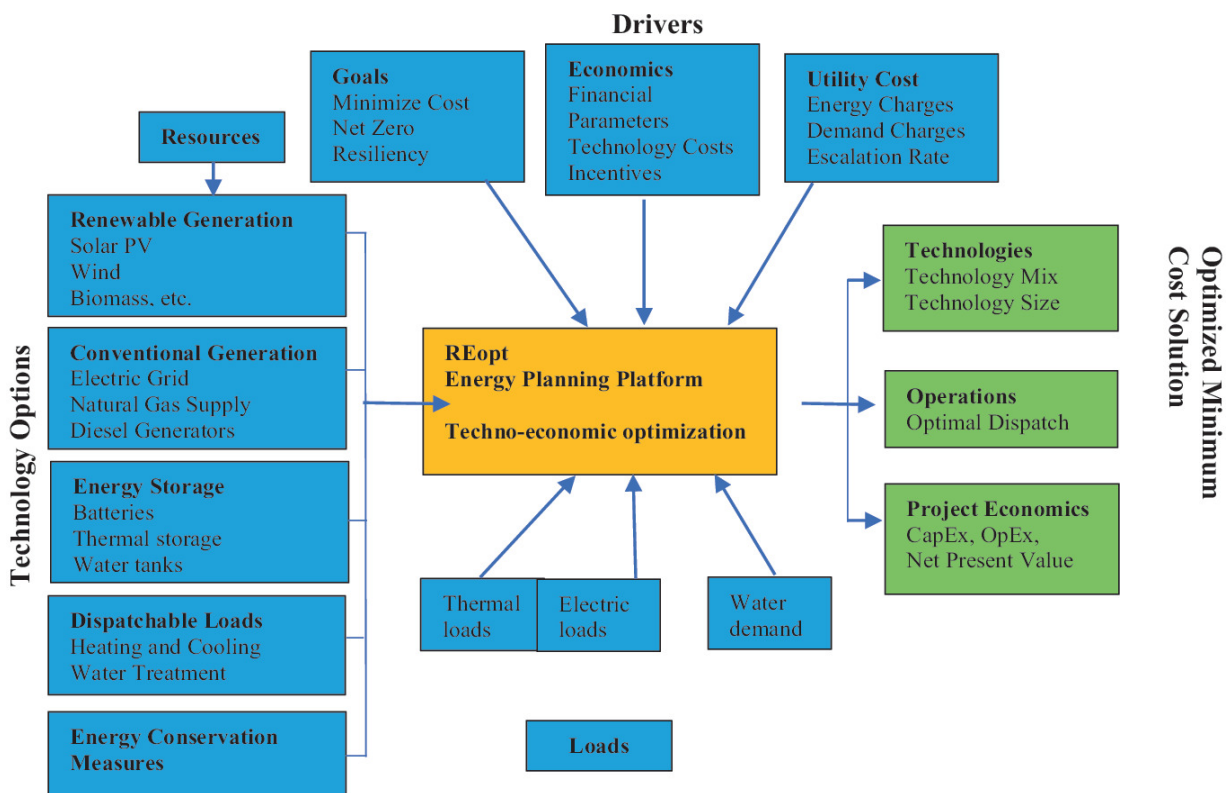


Fig. 1 Steps of the general research methodology through a summary of the main inputs and outputs of the REopt model.

Source Adapted from [45]

Within the 16 critical infrastructure sectors identified by the Presidential Policy Directive 21 (PPD-21): “Critical Infrastructure Security and Resilience” [46], stands out the consumption for information technology with a 14%, as well as the consumption for financial services, energy production, and healthcare and public health, each accounting for 10% of the total energy consumption of the 16 critical infrastructure sectors [47].

In the last ten years, the U.S. Northeast Corridor has had a large number of severe storms that which were the cause of major electrical outages [48–55]. Due to the justified importance of critical loads in healthcare and public health facilities, and the region's referenced large power outage problem, the research presented here will investigate the energy resilience benefits resulting from the utilization of solar PV, electrochemical batteries, cogeneration, TES water tanks, and absorption chillers for a hospital located in the U.S. Northeast Corridor. In particular, the applicability of the proposed solution at the Massachusetts General Hospital (MGH Gray Building), located in the city of Boston (USA), will be investigated. This section will describe the most important inputs to be introduced in the ReOpt Lite software (Appendix 1 shows in more detail the inputs used to conduct the research presented in this research paper). Appendix 2 shows electric load, heating system fuel load, cooling plant load, critical load, and emissions factor data. Finally, Appendix 3 presents CHP maintenance schedule. For research and analysis purposes the dispatch data are available as supplementary file in.csv format.

Load Profile analysis

The load profile has been simulated from actual data collected by the U.S. Department of Energy for Massachusetts General Hospital (which was published in

the Healthcare Energy End-Use Monitoring report [56]). Something to keep in mind when performing the simulation is that, unlike other types of users, hospitals usually have a high percentage of critical loads, on the order of 50% [57]. Estimated energy consumption is 39,684 MWh/year for MGH Gray Building [56]. Through the simulation performed by the Reopt Lite software, the average daily load for the MGH Gray Building is 4530,137 kW, with a minimum demand on December 25 and a maximum demand on August 4 (see Fig. 2). Following [57] the critical load for the MGH Gray Building is 50% of its total loads.

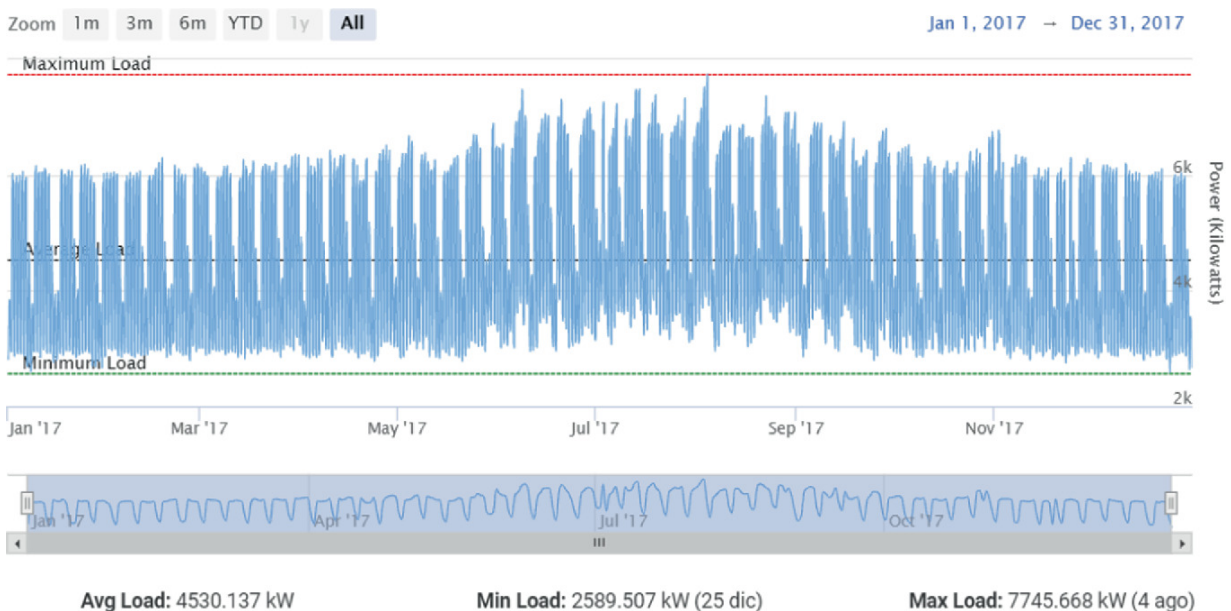


Fig. 2 Annual load demand for the Massachusetts General Hospital (MGH Gray Building, Boston)

Electric Rate

The research presented here has assumed that Massachusetts General Hospital maintains a contract with Eversource, which is the largest energy utility in New England [58]. Based on the characteristics and electrical consumptions of Massachusetts General Hospital, it has

been assumed that the rate used is the Greater Boston General Service G-2 (B2) [59].

Heating system fuel cost

Following as shown in [60], the research presented here will assume that the fuel cost of the existing boiler to supply the heating load is constant for all months of a single year. As shown in [61], the fuel cost has been assumed to have a value of \$1.50/MMBtu.

Cogeneration fuel cost

Following what is shown in [60], the research presented here will assume that the fuel cost of cogeneration is constant for all months of the same year. As shown in [62, 63] the assumed cogeneration fuel cost (natural gas) is \$6.50/MMBtu.

Solar cell panel for PV generation

The research presented here has assumed that the installation uses a bi-directional interface between the AC output circuits of the PV system and the grid [64–69]. Taking into account the system losses and those due to aging, the research presented here has followed the recommendation of the European Commission and used a value of 14% for the “system loss” [70]. Taking into account recent grey literature [71–74], the assumed lifetime of the solar PV system presented here is 25 years. This time period of 25 years will coincide, according to the specialized scientific literature [75], with the period of analysis considered. The hourly solar irradiation values used in the research presented here come from the TMY2 data of the National Solar Radiation Database 1991–2005 [45, 76]. Through the use of PVWatts software, Table 1

shows the average solar irradiance per kWh/m²/day for each month at Massachusetts General Hospital (MGH Gray Building, Boston).

Table 1 Average solar radiation per kWh/m²/day for each month at Massachusetts General Hospital (MGH Gray Building, Boston)

Month	Solar radiation (kWh/m ² /day)
January	3.13
February	3.98
March	4.72
April	5.44
June	6.20
July	6.49
August	5.94
September	5.25
October	4.00
November	2.92
December	2.58
Annual	4.72

Source [77]

Lithium-ion batteries

Energy storage through lithium-ion batteries plays an important role in overcoming the intermittency of renewable energy resources [78, 79]. The lowest desired charge level in lithium-ion batteries is usually 20%. In lithium-ion battery systems, it is important to adjust the state of charge of each cell to maximize the performance and longevity of the pack [80]. Cell life is improved by avoiding deep discharge, so, based on scientific literature [80], the state of charge has been limited to a minimum of 20%. Following the indications of current lithium-ion

battery manufacturers [81] and tests available in the classical scientific literature [82], an initial state of charge of 50% has been assumed. According to [73], it will be assumed that the battery and inverter will be in operation for 10 years, after which they will have to be replaced.

Cogeneration system (CHP)

The cogeneration performance model used is a generalized description of the relationships between cogeneration power and heat production and fuel input. These relationships are linearized and capture fuel consumption and available recoverable heat as a function of electrical load. All assumed prime movers are “topping cycles,” in which fuel is consumed in the generation of electricity, while excess heat from combustion can be captured to serve site thermal loads.

3 Results and Discussion

In order to carry out the optimization of the scheme through the Reopt Lite software, the first step would be to select the focus of the investigation. Of the two options offered by the Reopt Lite software, namely optimization for financial savings or for energy resilience improvement, the latter was selected. Once the approach was chosen, the next step was to select the technologies to be evaluated. With regard to the research presented here, the following technologies were evaluated:

- Photovoltaic solar panels
- Electrochemical batteries
- Wind generators
- Diesel generators acting as backup systems
- Combined heat and power generation through reciprocating internal combustion engines

- Combined heat and power generation through microturbines
- Combined heat and power generation through gas turbines
- Combined heat and power generation using fuel cells
- Thermal energy storage in the form of cold water and ice.

From all the possible combinations for the location and type of load studied, it turned out that, for an approach based on obtaining an improvement in energy resilience, the most suitable technologies were a combination of (i) solar photovoltaic panels; (ii) electrochemical batteries; (iii) combined heat and power generation through alternative internal combustion engines; and (iv) thermal energy storage in the form of cold water and ice. As a result, a microgrid containing a combination of these technologies has been selected for detailed analysis. All the inputs introduced to carry out the simulation are shown in Appendix 1.

3.1 Most Cost-Effective Combination to Sustain a Critical Load and Resilience Benefits at the Massachusetts General Hospital

Table 2 summarizes solar installation size, battery power and capacity, CHP electric capacity, absorption chiller cooling thermal capacity, chilled water TES tank size, and potential life cycle savings (25 years) at the Massachusetts General Hospital (MGH Gray Building, Boston).

Table 2 Resilience benefits

	Business as usual	Resilience parameters	Financial
System	None	238 kW PV	238 kW PV
		13 kW battery	12 kW battery
		30 kWh battery	29 kWh battery
		5519 kW CHP	5522 kW CHP
		1025,090 gal chilled water storage	973,314 gal chilled water storage
		1203 ton absorption chiller	1210 ton absorption chiller
NPV	\$0	\$65,628,837	\$65,655,559
Survives specified outage	No	Yes	No

Source Own Elaboration

This system was designed to sustain the critical load during the outage period specified at lowest cost. The results below show how the system performs during outages occurring at other times of the year. Outages are simulated starting at every hour of the year and amount of time the system can sustain the critical load during each outage is calculated. The resilient system is compared to the business as usual system and a system designed for maximum financial benefits.

Following Table 2, the “resilient system” is the only one able to sustain the 50% critical load during the specified outage period, from August 4 at 4 pm to August 4 at 8 pm.

3.2 System Performance Year One and Effect of Resilience Costs and Benefits

In this section the global system performance is studied for the first year and the most important aspects in terms of energy performance and the impact of the outage period.

3.2.1 Dispatch Strategy Optimized for the Specified Outage Period as Well as the Rest of the Year

The proposed methodology ensures a global dispatch optimization considering both the specific outage period and the whole year cycle. The outage period is analyzed for the 4-h period ranging from 4 to 8 pm on August 4.

Figure 3 shows the system performance in first year for the period from August 3 to August 6.

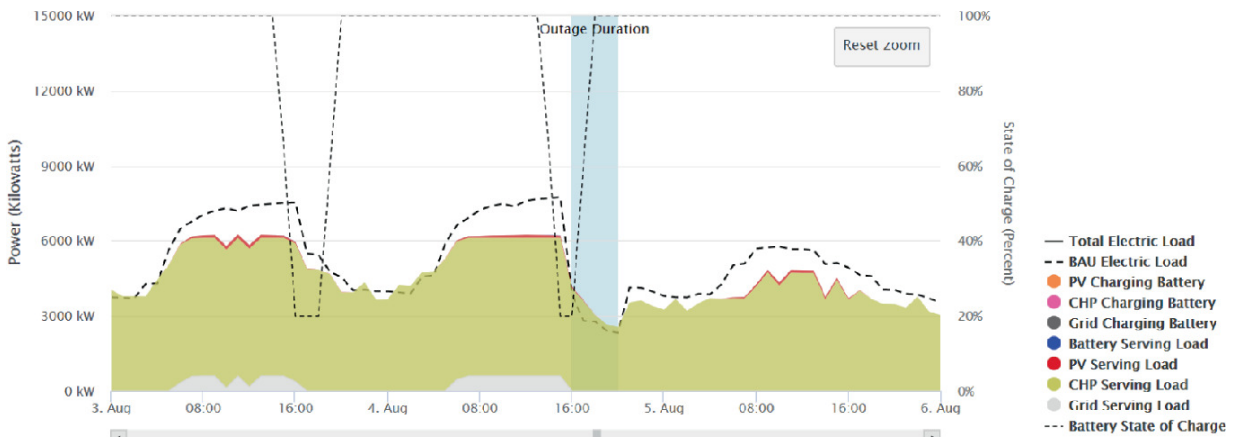


Fig. 3 Dispatch strategy optimized for the specified outage period as well as the rest of the year

As shown in Fig. 3 the grid serving load during the outage is zero and, despite it, the system ensures the correct power supply in the studied hospital facility. During the outage and following hours there is almost no available instantaneous PV production as a consequence of optimal energy storage strategy. Despite complete lack of grid connection, the optimized system can provide the required energy for critical loads and ensure that battery state of charge recovers the required levels after the outage, ensuring system stability for upcoming hours.

3.2.2 Thermal Dispatch Strategy Optimized

Thermal requirements are critical in the studied facility and, therefore, the Reopt Lite sizing option used in this research aims to ensure resilience. Figure 4 shows optimal operation of the CHP system where the topping cycle strategy ensures power generation (as shown in Fig. 3 for the outage period) and excess heat can be used for heat load supply, as proved in Fig. 4. During normal operation the system uses a control strategy that allows serving the building thermal load but also storage energy in the thermal storage systems. If the system is correctly sized, designed and managed, during the outage period with a duration of 4 h, the total heating load should be supplied and, if required, storage heat must be used to match demand. As depicted in Fig. 4 the whole system is in equilibrium and the outage does not impact in the heating operational characteristic, proving the optimal heating resilience of the hospital facility.

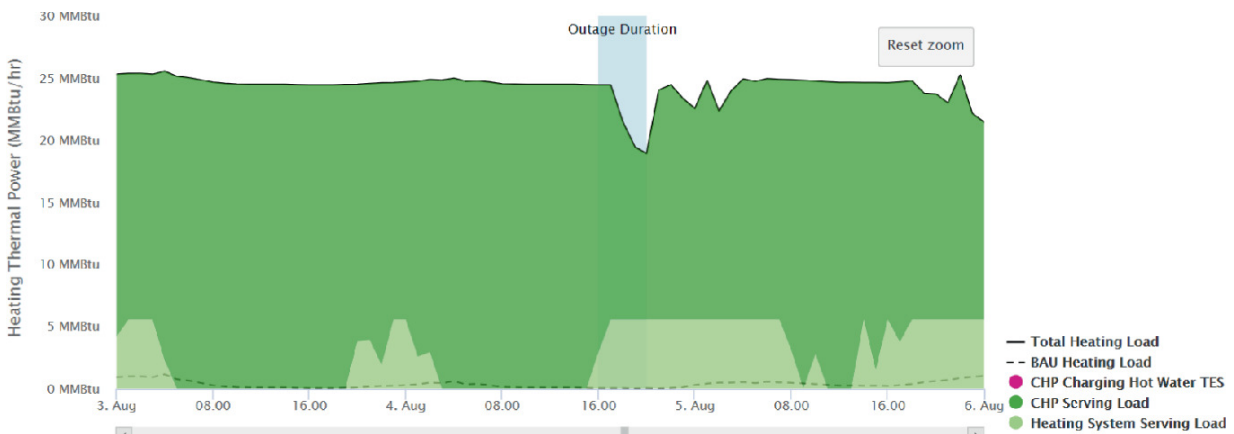


Fig. 4 Thermal dispatch strategy optimized

3.2.3 Cooling Thermal Dispatch Strategy Optimized

Cooling systems are critical in hospitals due to its importance in many critical services including climatization, critical unit temperature maintenance and humidity control, among others.

The hospital uses a combination of electrical chillers and absorption chillers that are optimized in terms of energy efficiency and resilience. Combination of both compression and absorption chillers allows optimal use of thermal generation and allows that CHP can follow a topping strategy and excess heat can be used for cool production that can be instantly used in the hospital or used for TES system load. Figure 5 shows the operation during three days where can be seen the previous strategy that optimizes energy usage and the TES charge and discharge cycles. Considering the optimal resilience sizing and control strategy, in the outage period (4 pm–8 pm) the critical electrical load requirements reduces cooling load to zero and therefore all the available thermal and electrical power is used to charge the TES system.

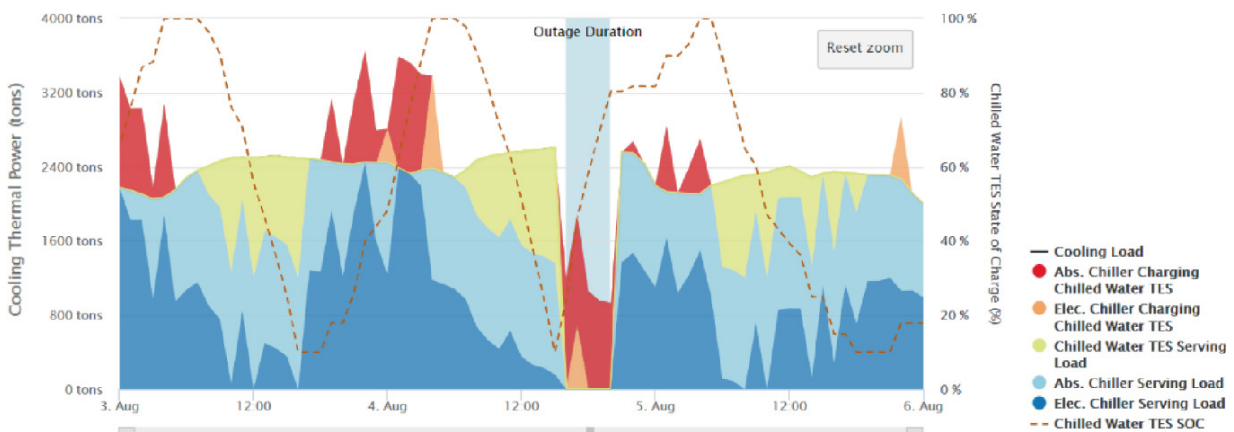


Fig. 5 Cooling thermal dispatch strategy optimized

3.2.4 Reduction in Peak Load that Occurs When the Recommended Technologies Are Implemented

The heat—demand duration curves are shown in Fig. 6 for the conventional case and for the optimal sizing. Considering a general case exist a required net side load the whole year (up to 8760 h in case of continuous operation, such as in a hospital) reducing resilience of the

system because it lacks any possibility of self-operation. Using a resilient sizing strategy, and the combined control strategy, two important effects are obtained: peak demand is lowered, and cumulative hours are lowered up to less than 1000 h. This combined effect increases resilience and guarantee operational feasibility in case of no availability of grid connection. Moreover, in terms of economic impact, peak demand costs (grid access) are reduced.

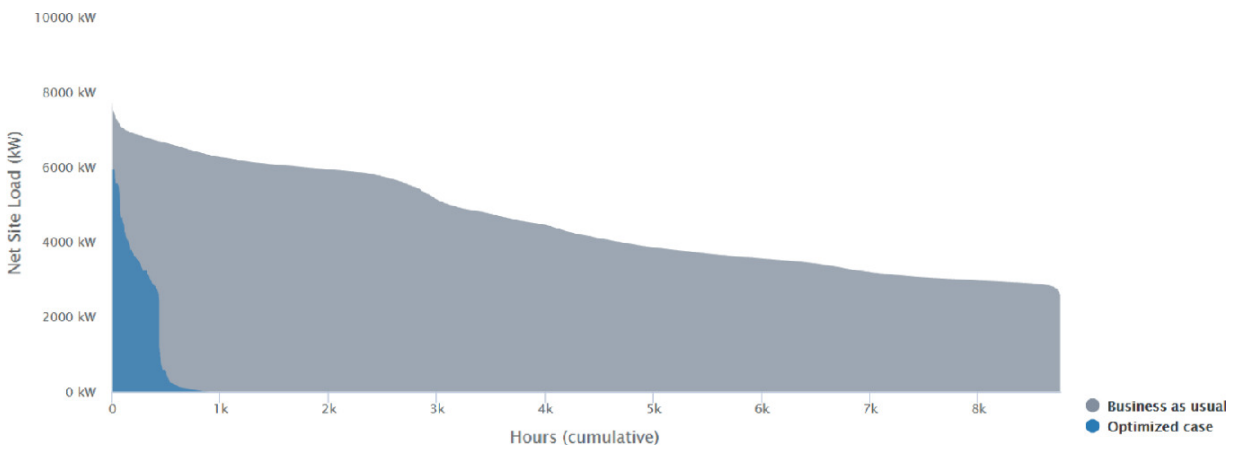


Fig. 6 Reduction in peak load throughout the year? that occurs when the recommended technologies are implemented

The cooling and thermal systems operation and power supply are shown in Fig. 7. The operational strategy of the whole system is presented, proving the ability of the resilient microgrid to maintain critical loads operation during the outage period.

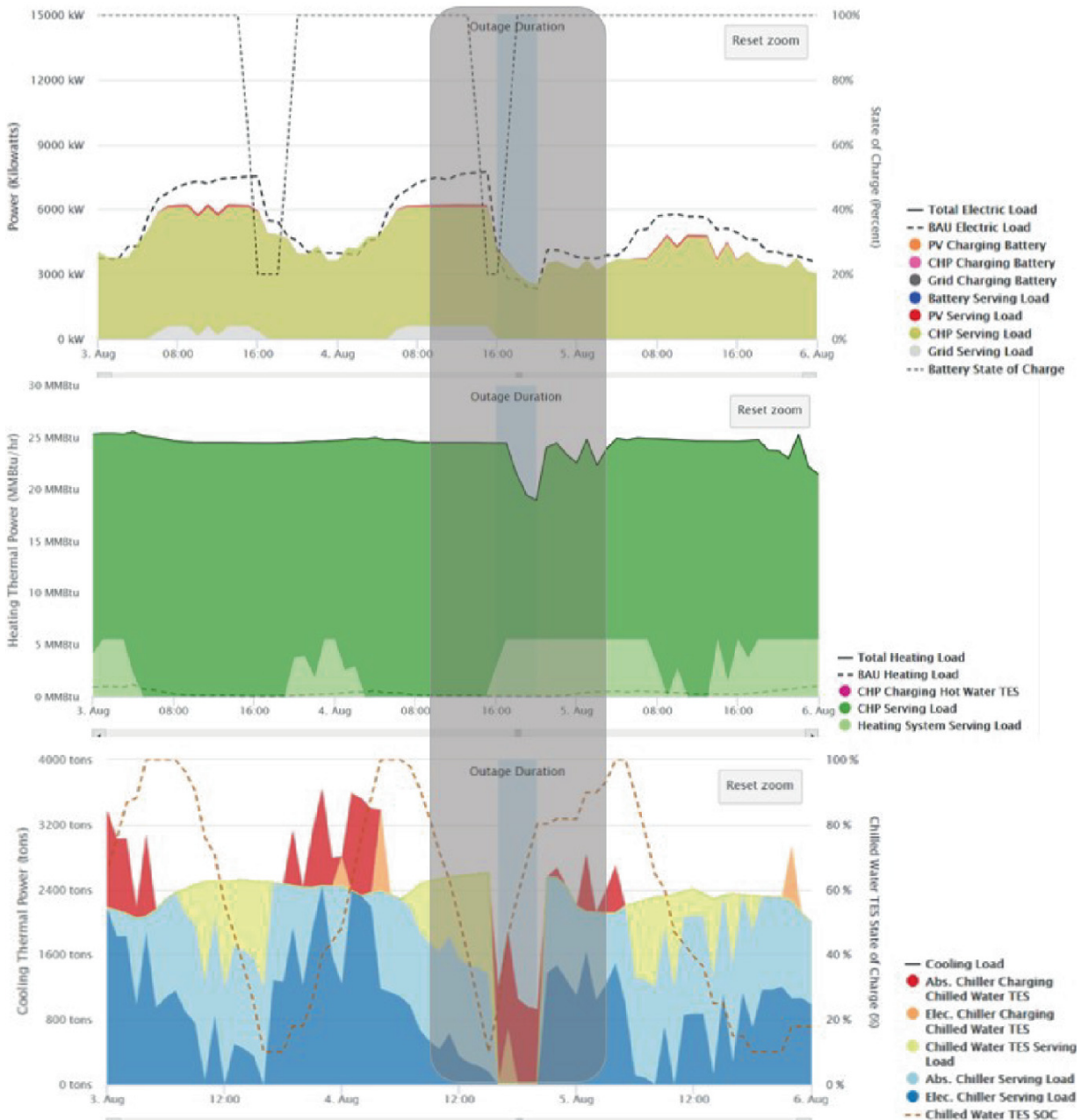


Fig. 7 Power, thermal power and cooling thermal power during outage

3.2.5 Effect of Resilience Costs and Benefits

In order to gain resiliency, the PV/wind/battery/generator must be installed as an island-able system. This incurs additional costs above a typical grid-connected system, which are not included in the economics of the Reopt Lite primary optimization. Depending on current site

equipment, additional components required may include a manual or automatic transfer switch, critical load panel, and additional controls capabilities in the inverter for islanded operation. For the research here presented, it has been considered that microgrid upgrade cost reaches a 30% of system capital cost.

In spite of the avoided outage cost is not factored into the Reopt lite optimization, it is an important factor to evaluate correctly costs and benefits. Following data from the existing literature [83–85], for the research here presented, it has been considered that avoided outage costs reaches \$100 per kWh. From Fig. 7 it is possible to see how, in the event of an outage at the Massachusetts General Hospital (MGH Gray Building), there will be monetary effects that will last longer than the duration of the outage. NPV before microgrid investment, microgrid upgrade costs, avoided outage costs, and NPV after microgrid costs and benefits are presented in Fig. 8.

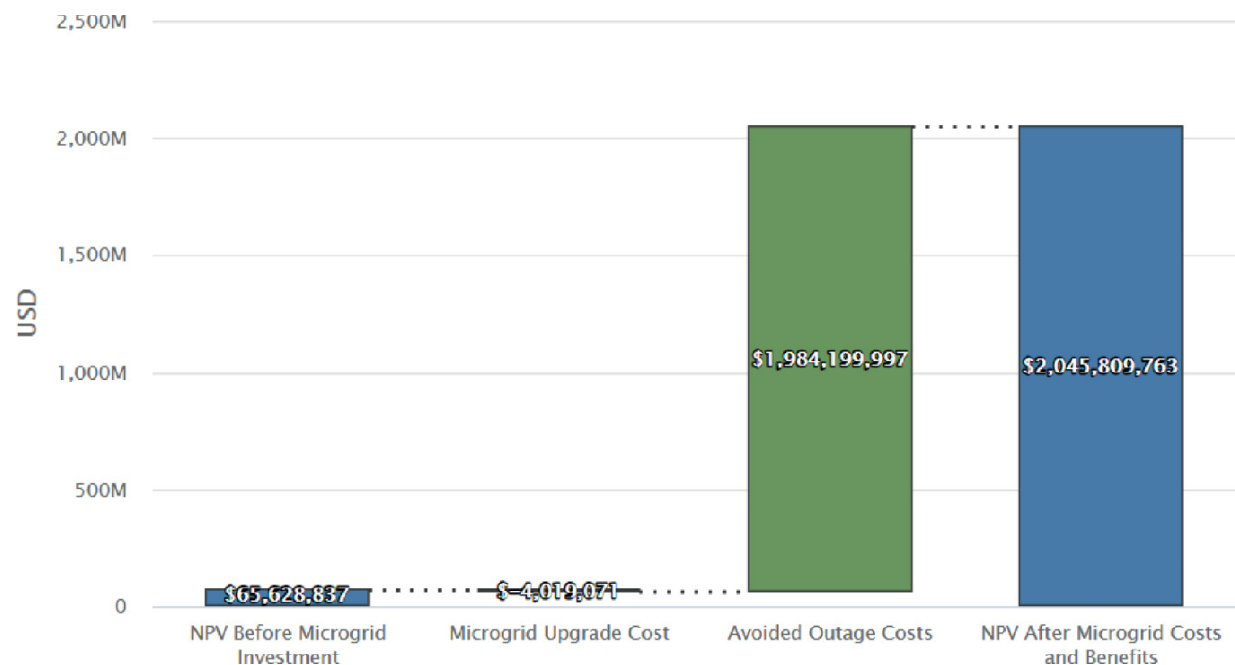


Fig. 8 Effect of resilience costs and benefits

Supplementary material includes a detailed breakdown of inputs and outputs, optimal cash flow and BAU cash flow.

4 Conclusions

Microgrids are becoming one of the key solutions for distributed energy systems and in the transition process to decarbonized systems but they can offer other additional advantages, being increased resilience one of the most important especially in facilities with critical loads.

Combining an optimally sized microgrid with an optimal control system it is possible to reduce peak loads the microgrid and obtaining benefits in terms of energy resilience. A polygeneration microgrid using both renewable and not renewable sources, including solar PV, cogeneration, absorption chillers and hybrid energy storage systems (TES water tanks and electrochemical batteries) is proposed under an optimized sizing scheme. In terms of control system, the associated specific control systems to provide correct power quality for local loads and ensures maximum resilience of the system.

For the presented case study, a critical facility (hospital) the plant and control design are presented and the technical and economic benefits are analyzed. Dispatch optimization of both the specific outage period and the whole year cycle is presented and results show that despite lack of grid power supply the optimized system match the critical loads demand and that battery state of charge recovers nominal levels after the outage, ensuring system stability for upcoming hours.

The resilience is achieved using a hybrid PV/wind/battery/generator with the capacity to work as a completely islanded systems, what increases the investment costs in comparison with a conventional grid-connected system. The capacity to supply power as a

completely isolated grid requires additional power components and control devices, increasing the system capital cost but the avoided outage last longer than the duration of the outage. For critical facilities, as the hospital presented in this research, there are many additional benefits to be considered that are difficult to account in terms of economic benefits: this includes critical services security and resilience, that must be considered.

Results show that hybrid microgrids can be used as part a decarbonization roadmap but also, if resilience parameters are considered in the design phase, can provide a resilient system for critical loads. The methodology and results can be applied for similar facilities and adapted to different case studies and validates the resilient design of microgrids.

Acknowledgements

The authors gratefully acknowledge the support of Center for Industrial Technological Development (CDTI) through its “Proyectos Transferencia Cervera” research program, without which the present study could not have been completed. This work has been supported by the Center for Industrial Technological Development, Spain (Project HysGrid+ “Desarrollo de Comunidades Locales Energéticamente Positivas con Sistemas Híbridos de Generación Renovable y Almacenamiento”, CER20191019).

Appendix 1: Inputs Site Data

<i>Site and utility</i>	
Site location	Boston, Massachussetts, EEUU
Electricity rate	NSTAR Co d/b/a Eversource Energy: Greater Boston General Service G-2 (B2)
Annual existing heating system fuel cost (\$/MMBtu)	1.5

Annual CHP fuel cost (\$/MMBtu)	6.5
Fuel	
Existing heating system efficiency (% HHV-basis)	80%
Max. boiler thermal capacity as factor of peak heating load	1.25
Existing heating system fuel type	Natural gas
CHP fuel type	Natural gas
Solver settings	
Solver optimality tolerance (%)	1.0%
<i>Load profiles</i>	
Typical electrical load	
Type of building	Hospital
Annual energy consumption (kWh)	39,684,000
Electrical load adjustment	
Adjust electricity consumption	100% of original consumption
Typical heating system fuel load	
Type of building	Hospital
Annual heating system fuel consumption (MMBtu)	13,070
Addressable load percent (%)	100%
Typical cooling system thermal load	
Type of building	Hospital
Electric cooling plant coeff. of performance (kWt/kWe)	4.69
Max. chiller thermal capacity as factor of peak cooling load	1.25
<i>Resilience</i>	
Critical electric load	
Critical load factor (%)	50
Outage information	

Outage duration (hours)	4
Outage start date	August 4
Outage start time	4 pm
<i>Effect of resilience costs and benefits</i>	
Microgrid upgrade cost	30%
Avoided outage costs	\$100 per kWh
<i>Financial</i>	
Analysis period (years)	25
Host discount rate, nominal (%)	8.3%
Electricity cost escalation rate, nominal (%)	2.3%
Existing heating system fuel cost escalation rate, nominal (%)	3.4%
CHP fuel cost escalation rate, nominal (%)	3.4%
Host effective tax rate (%)	26%
O&M cost escalation rate (%)	2.5%
<i>Emissions</i>	
<i>Electricity grid emissions factors</i>	
Source of hourly grid emissions factors	US EPA AVERT Northeast Region
<i>Fuel emissions factors</i>	
Heating system natural gas emissions factor (lbs CO ₂ /MMBtu)	116.9
CHP natural gas emissions factor (lbs CO ₂ /MMBtu)	116.9
<i>PV</i>	
System capital cost (\$/kW DC)	\$1600
Minimum new PV size (kW DC)	0
Maximum new PV size (kW DC)	Unlimited

<i>PV costs</i>	
O&M cost (\$/kW per year)	\$16
<i>PV system characteristics</i>	
Module type	Standard
Array type	Ground mount, fixed
Array azimuth (deg)	180
Array tilt (deg)	42.36
DC to AC size ratio	1.2
System losses (%)	14%
PV station search radius (mi)	Unlimited
<i>Location</i>	
PV & wind space available	Roofspace only
Roofspace available (sq ft)	23 761 ft ² [86]
<i>Tax treatment</i>	
MACRS schedule	5 years
MACRS bonus depreciation	100%
<i>Battery</i>	
Energy capacity cost (\$/kWh)	\$420
Power capacity cost (\$/kW AC)	\$840
Allow grid to charge battery	Yes
Minimum energy capacity (kWh)	0
Maximum energy capacity (kWh)	Unlimited
<i>Battery costs</i>	
Energy capacity replacement cost (\$/kWh)	\$200
Energy capacity replacement year	10
Power capacity replacement cost (\$/kW AC)	\$410
Power capacity replacement year	10

<i>Battery characteristics</i>	
Minimum power capacity (kW AC)	0
Maximum power capacity (kW AC)	Unlimited
Rectifier efficiency (%)	96%
Round trip efficiency (%)	97.5%
Inverter efficiency (%)	96%
Total AC-AC round trip efficiency	89.9%
Minimum state of charge (%)	20%
Initial state of charge (%)	50%
<i>Battery incentives and tax treatment</i>	
Total percentage-based incentive (%)	0%
Total power capacity rebate (\$/kW)	\$0
MACRS schedule	7 years
MACRS bonus depreciation	100%
<i>Wind</i>	
Size class	Commercial (21-100 kW)
System capital cost (\$/kW AC)	\$7390
Minimum size desired (kW AC)	0
Maximum size desired (kW AC)	Unlimited
<i>Wind costs</i>	
O&M cost (\$/kW per year)	\$40
<i>Tax treatment</i>	
MACRS schedule	5 years
MACRS bonus depreciation	100%
<i>Generator</i>	
Install cost (\$/kW AC)	\$500
Diesel cost (\$/gal)	\$3
Fuel availability (gallons)	660

Minimum new generator size (kW AC)	0
Maximum new generator size (kW AC)	Unlimited
Generator costs	
Fixed O&M cost (\$/kW per year)	\$10
Variable O&M cost (\$/kWh)	\$0.00
Generator characteristics	
Fuel burn rate (gallons/kWh)	0.076
Fuel consumption curve y-intercept (gallons/hour)	0.000
<i>Combined heat and power</i>	
Prime mover	
Prime mover type	Reciprocating engine
Size class	Size Class 2 (100-630 kW) CHP electric capacity sized based on the average heating load for all 8760 h of the year = 282 kW (Size Class 2)
Minimum electric power capacity (kW)	0
Minimum non-zero power capacity (kW)	50
Maximum electric power capacity (kW)	10,000
CHP costs	
Fixed O&M cost (\$/kW/yr)	\$0.0
Variable O&M cost (\$/kWh)	\$0.022
CHP system characteristics	
Electric efficiency at 100% load (% HHV-basis)	32.1%
Electric efficiency at 50% load (% HHV-basis)	32.1%
Thermal efficiency at 100% load (% HHV-basis)	49.3%

Thermal efficiency at 50% load (% HHV-basis)	49.3%
Min. electric loading of prime mover (% of rated electric capacity)	50%
Knockdown factor for CHP-supplied thermal to absorption chiller (%)	80.0%
<i>Tax treatment</i>	
MACRS schedule	5 years
MACRS bonus depreciation	100%
<i>Absorption chiller</i>	
<i>Absorption chilling</i>	
Minimum size (ton)	0
Maximum size (ton)	Unlimited
Total installed cost (\$/ton)	1248.00
<i>Absorption chiller costs</i>	
Fixed O&M cost (\$/ton/yr)	18.00
<i>Absorption chiller system characteristics</i>	
Coefficient of performance (COP)	0.74
Electric consumption COP for heat rejection (kWt/kWe)	14.1
<i>Tax treatment</i>	
MACRS schedule	No MACRS
MACRS bonus depreciation	100%
<i>Chilled water storage</i>	
Minimum size (gal)	0
Maximum size (gal)	Unlimited
Total installed cost (\$/gal)	\$1.50
Chilled supply water temperature (°F)	44.0
Return water temperature (°F)	56.0
Fixed O&M cost (\$/gal/yr)	0

Thermal loss rate (% of energy storage capacity per hour)	0.04%
Minimum state of charge (%)	10%
<i>Tax treatment</i>	
MACRS schedule	No MARCS
MACRS bonus depreciation	100%

Appendix 2. Electric Load, Heating System Fuel Load, Cooling Plant Load, Critical Load, and Emissions Factor Data

See Figs. 9, 10, 11, 12 and 13.



Fig. 9 Electric load data

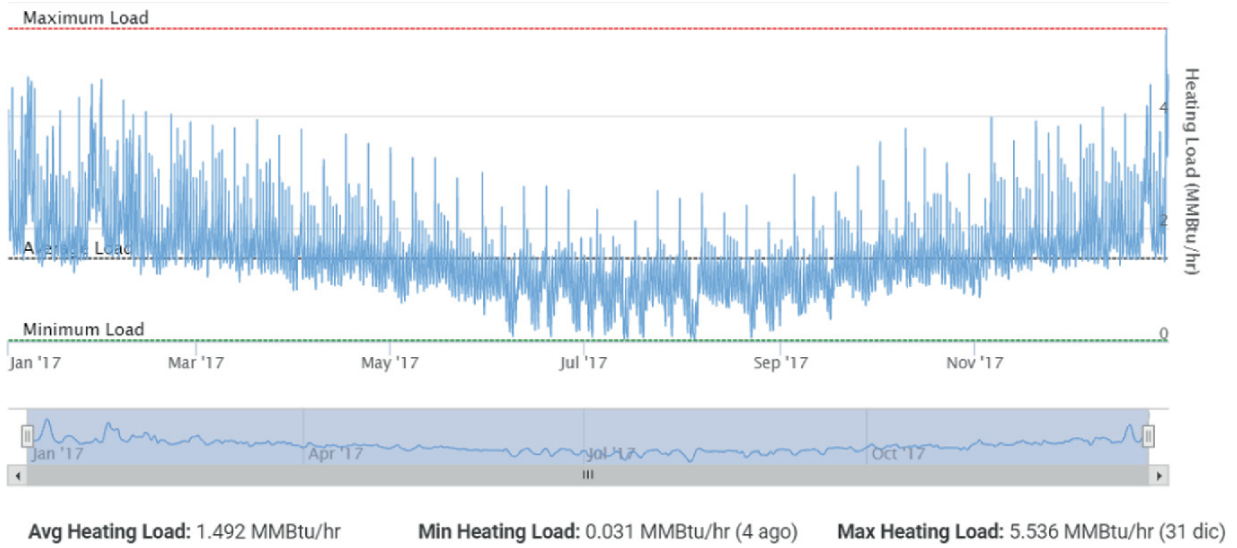


Fig. 10 Heating system fuel load data

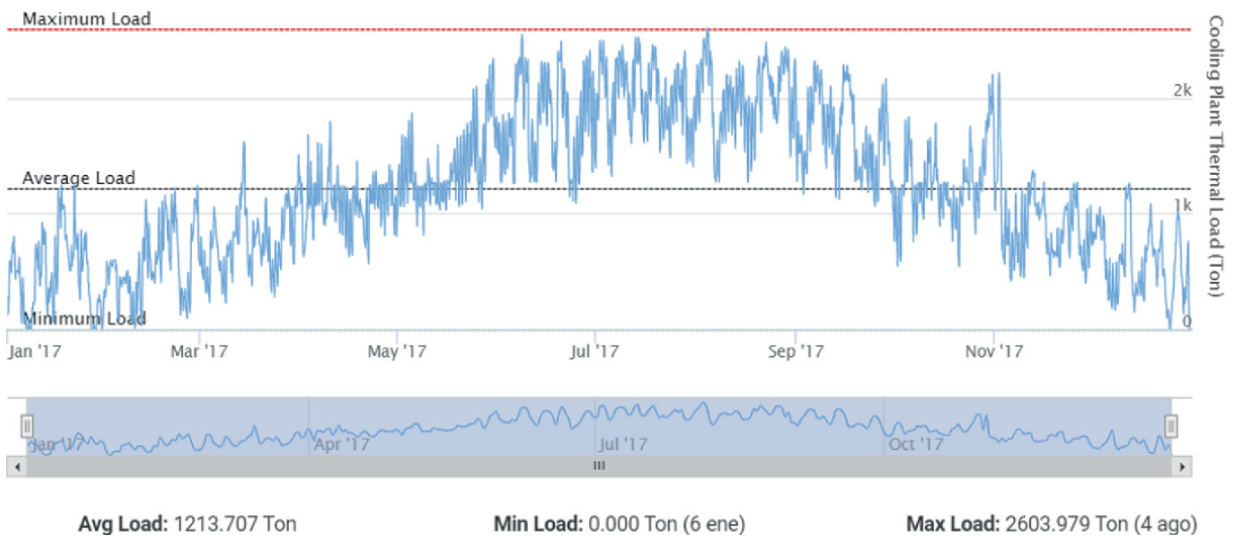


Fig. 11 Cooling plant load data

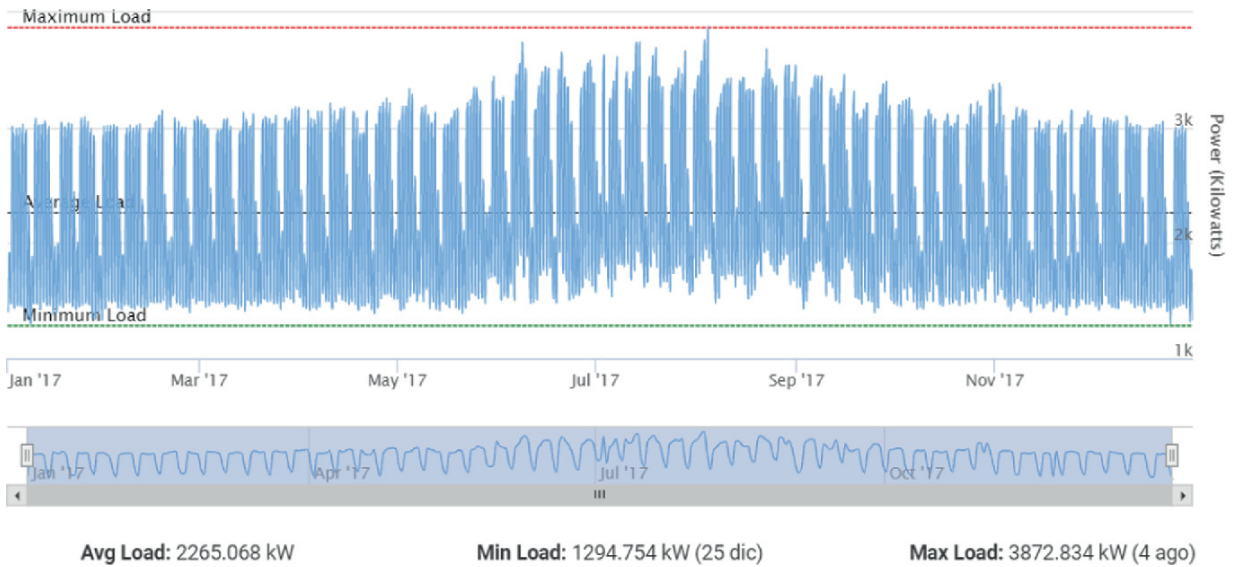


Fig. 12 Critical load data

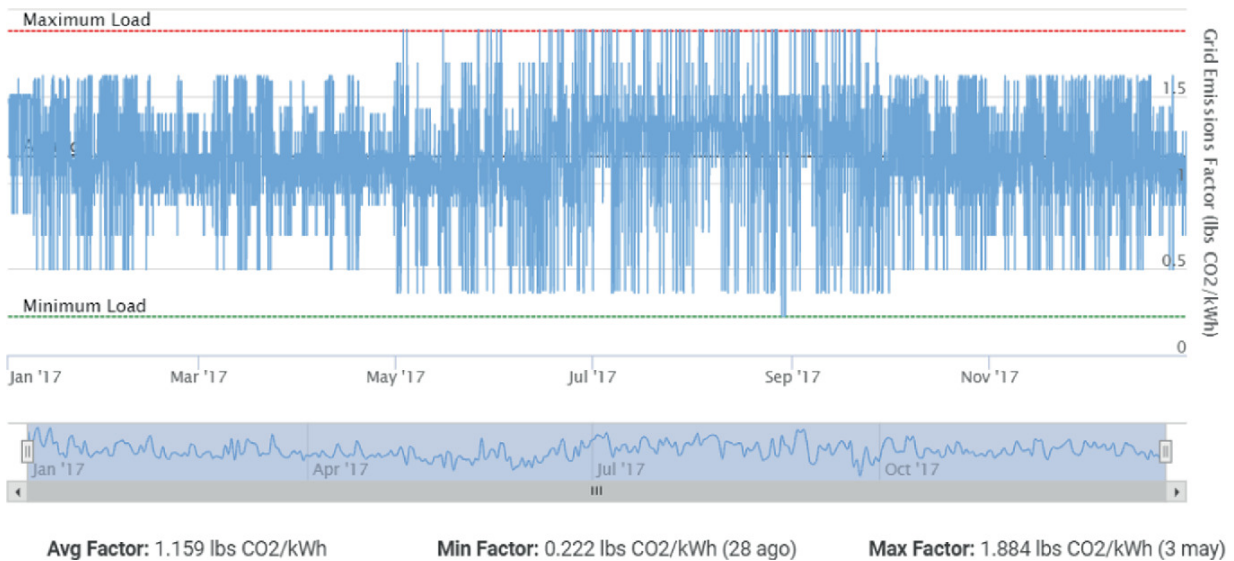


Fig. 13 Emissions factor data

Appendix 3: CHP Maintenance Schedule

Maintenance Periods		
Start Date & Time	End Date & Time	Length (hrs)
01/07/2017 Saturday 12:00 am	01/09/2017 Monday 12:00 am	48
02/06/2017 Monday 12:00 am	02/08/2017 Wednesday 12:00 am	48
03/11/2017 Saturday 12:00 am	03/13/2017 Monday 12:00 am	48
05/13/2017 Saturday 12:00 am	05/15/2017 Monday 12:00 am	48
06/05/2017 Monday 12:00 am	06/07/2017 Wednesday 12:00 am	48
07/08/2017 Saturday 12:00 am	07/10/2017 Monday 12:00 am	48
09/09/2017 Saturday 12:00 am	09/11/2017 Monday 12:00 am	48
10/02/2017 Monday 12:00 am	10/04/2017 Wednesday 12:00 am	48
11/11/2017 Saturday 12:00 am	11/13/2017 Monday 12:00 am	48

References

1. Jesse BJ, Heinrichs H, Kuckshinrichs W (2019) Adapting the theory of resilience to energy systems: a review and outlook. *Energy Sustain Soc* 9(27):1–19
2. World Health Organization. More people have access to electricity than ever before, but world is falling short of sustainable energy goals. <https://www.who.int/news/item/21-05-2019-more-people-have-access-to-electricity-than-ever-before-but-world-is-falling-short-of-sustainable-energy-goals>. Accessed 15 Sept 2021
3. United Nations Statistics Division Development Data and Outreach Branch. Ensure access to affordable, reliable, sustainable and modern energy for all. <https://unstats.un.org/sdgs/report/2019/goal-07/>. Accessed 15 Sept 2021
4. FUERGY. 7 major challenges of a power grid and their solutions. <https://fuergy.com/blog/7-problems-and-challenges-of-a-power-grid>. Accessed 15 Sept 2021
5. Busby JW, Baker K, Bazilian MD, Gilbert AQ, Grubert E, Rai V et al (2021) Cascading risks: understanding the 2021 winter blackout in Texas author links open overlay panel. *Energy Res Soc Sci* 77:102106 [Crossref]

6. Modesto Irrigation District. Power outages: tips and resources for businesses. <https://www.mid.org/edusafety/beprepared/bus.htm>. Accessed 15 Sept 2021
7. Kenward A, Raja U (2014) Blackout: extreme weather, climate change and power outages. Princeton, Climate Central
8. Bisaro A, Rokitzki M, Hofemeier A (2020) Climate impact induced crisis in Europe: an exploration of scenarios. Heinrich Böll Foundation/Finanzwende, Berlin
9. Wing IS, Rose AZ (2020) Economic consequence analysis of electric power infrastructure disruptions: general equilibrium approaches. *Energy Econ* 89:104756
[Crossref]
10. Oppedisano D (2019) A case study on emergency backup power with renewable energy. University of British Columbia, Vancouver
11. García-Vera YE, Dufo-López R, Bernal-Agustín JL (2019) Energy management in microgrids with renewable energy sources: a literature review. *Appl Sci* 9:3854
[Crossref]
12. Bidram A, Lewis FL, Davoudi A (2014) Distributed control systems for small-scale power networks: using multiagent cooperative control theory. *IEEE Control Syst Mag* 34(6):56–77
[MathSciNet][Crossref]
13. Kumar GVB, Palanisamy K (2020) A review of energy storage participation for ancillary services in a microgrid environment. *Inventions* 5:63
[Crossref]
14. Kempener R, Lavagne-d'Ortigue O, Saygin D, Skeer J, Vinci S, Gielen D (2014) Off-grid renewable energy systems: status and methodological issues. IRENA, Berlin
15. SMO Energy. Why buy a standby generator? <https://smoenergy.com/blog/why-buy-a-standby-generator/>. Accessed 21 Sept 2021
16. Power Products Systems. How Long Will a Standby Generator Last? <https://www.standbygeneratorsne.com/blog/how-long-will-a-standby-generator-last/>. Accessed 21 Sept 2021
17. CK Power. Prime power generators: Everything you need to know about prime power generators, <https://www.ckpower.com/everything-you-need-to-know-about-prime-power-generators/>. Accessed 21 Sept 2021

18. IRENA (2012) Electricity storage and renewables for island power: a guide for decision makers. International Renewable Energy Agency, Abu Dhabi
19. Boretti A, Castelletto S, Al-Kouz W, Nayfeh J (2020) Capacity factors of solar photovoltaic energy facilities in California, annual mean and variability. In: E3S web of conferences, vol 181, p 02004. ICSREE 2020
20. Fitzgerald G, Mandel J, Morris J, Touati H (2017) The economics of battery energy storage: How multi-use, customer-sited batteries deliver the most services and value to customers and the grid. Rocky Mountain Institute, Basalt
21. Masrur H, Senjyu T, Islam MR, Kouzani AZ, Mahmud MAP (2020) Optimal operation of resilient microgrids during grid outages. In: IEEE international conference on applied superconductivity and electromagnetic devices (ASEMD), pp 1-2
22. Razeghi G, Gu F, Neal R, Samuelsen S (2018) A generic microgrid controller: concept, testing, and insights. Appl Energy 229:660-671
[Crossref]
23. Teimourzadeh S, Tor OB, Cebeci ME, Bara A, Oprea SV (2019) A three-stage approach for resilience-constrained scheduling of networked microgrids. J Mod Pow Syst Clean Energy 7:705-715
[Crossref]
24. Arghandeh R, Brown M, Del Rosso A, Ghatikar G, Stewart E, Vojdani A et al (2014) The local team leveraging distributed resources to improve resilience. IEEE Power Energy Mag 12:76-83
[Crossref]
25. Liu Y, Fan R, Terzija V (2016) Power system restoration: a literature review from 2006 to 2016. J Mod Power Syst Clean Energy 4:332-341
[Crossref]
26. IRENA (2020) Renewable power generation costs in 2019. International Renewable Energy Agency. IRENA, Abu Dhabi
27. Celtic Energy (2017) Resilient microgrids for Rhode Island critical services. RI Office of Energy Resources, One Capitol Hill
28. Route One Publishing. Microgrids & the new power generation. <https://www.itsinternational.com/feature/microgrids-new-power-generation>. Accessed 28 Sept 2021
29. Iberdrola. Using the clean energy sources close to you, https://www.iberdrola.com/wcorp/gc/prod/es_ES/sostenibilidad/docs/Micro_Grid_Sizing_Leaflet.pdf. Accessed 28 Sept 2021

30. Natural Hazards Center. Lives on the line: The big benefits of microgrids in disaster, <https://hazards.colorado.edu/news/research?page=4>. Accessed 28 Sept 2021
31. Kjølle GH, Utne IB (2010) Critical infrastructures and risk analysis of electricity supply. ESREL, Rhodes, 6–10 Sept 2010
32. Transportation and Infrastructure Committee, U.S. House of Representatives (2016) Blackout! Are we prepared to manage the aftermath of a cyber-attack or other failure of the electrical grid? Transportation and Infrastructure Committee, U.S. House of Representatives; Washington
33. Mabee M (2021) Request for information (RFI) on ensuring the continued security of the United States critical electric infrastructure. Department of Energy, Washington
34. Vichova K, Hromada M (2019) The evaluation system to ensure the transport of emergency supplies of fuel to the hospitals. Transp Res Procedia 40:1618–1624
[Crossref]
35. Brännlund R, Value of lost load some issues and reflections. Umeå School of Business and Economics, Umeå. <https://energiforskmedia.blob.core.windows.net/media/24384/p9-value-of-lost-load-brannlund.pdf>. Accessed 28 Sept 2021
36. London Economics International for ERCOT (2013) Estimating the Value of Lost Load: Briefing paper prepared for ERCOT by LEI
37. Kurnik C, Voss P (2020) Financing microgrids in the federal sector. U.S. Department of Energy, Washington
38. Marqusee J, Becker W, Ericson S (2021) Resilience and economics of microgrids with PV, battery storage, and networked diesel generators. Adv Appl Energy 3:100049
[Crossref]
39. Marqusee J, Ericson S, Jenket D (2021) Impact of emergency diesel generator reliability on microgrids and building-tied systems. Appl Energy 285:116437
[Crossref]
40. Laws ND, Anderson K, DiOrio NA, Li X, McLaren J (2018) Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings. Renew Energy 127:896–909
[Crossref]

41. Kwasnik T, Elgqvist E, Anderson K (2020) Assessing uncertainty in the timing of energy use during cost-optimal distributed energy technology selection and sizing. *Renew Energy Focus* 35:122–131
[Crossref]
42. Linkov I, Trump BD, Hynes W (2019) Resilience-based strategies and policies to address systemic risks. Organisation for Economic Co-operation and Development, Paris
43. Legal Information Institute. Energy resilience, https://www.law.cornell.edu/definitions/uscode.php?width=840&height=800&iframe=true&def_id=10-USC-1624767337-428117824&term_occur=1&term_src=title:10:subtitle:A:part:I:chapter:1:section:101. Accessed 3 Oct 2021
44. Panteli M, Mancarella P, Trakas DN, Kyriakides E, Hatziargyriou N (2017) Metrics and quantification of operational and infrastructure resilience in power systems. *IEEE Trans Power Syst* 32(6):4732–4742
[Crossref]
45. Cutler D, Olis D, Elgqvist E, Li X, Laws N, DiOrio N et al (2017) REopt: a platform for energy system integration and optimization. National Renewable Energy Laboratory, Golden
46. Cybersecurity and Infrastructure Security Agency. Critical infrastructure sectors, <https://www.cisa.gov/critical-infrastructure-sectors>. Accessed 4 Oct 2021
47. Northern Ohio InfraGard Members Alliance. Critical infrastructure, <https://nocinfragard.org/critical-infrastructure>. Accessed 4 Oct 2021
48. The Washington Post. Remembering 2010’s Snowmageddon in 10 images and scenes, <https://www.washingtonpost.com/weather/2019/02/05/remembering-s-snowmageddon-images-scenes/>. Accessed 4 Oct 2021
49. National Oceanic and Atmospheric Administration. This month in climate history: February 4–7, 2010, Blizzard, <https://www.ncdc.noaa.gov/news/month-climate-history-february-4%E2%80%937-2010-blizzard>. Accessed 4 Oct 2021
50. Babay E, Storm downs trees, cutting power to over 300,000 homes, https://news.yahoo.com/storm-downs-trees-cutting-power-040000731.html?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmVzLw&guce_referrer_sig=AQAAACmitQuJ7Vft86Hul0Om53V0PzP-CDDGDizJOxrTkDHSmoTbbtly5cb5yNifmiY8s-u6Ehk3jIJDzeR01JPgMkUS_bjnKz8iZXEZebL6ylhfA-qgFqZWj0EwOaRbQpysz3I5IX7QmlPOXaDxubW_-WnzDfgEQZLPz9uhiuk3E9kV. Accessed 5 Oct 2021

51. Pepco. Summer storms—July, August 2010, <https://www.washingtonpost.com/wp-srv/metro/Pepcostormresponse.PDF>. Accessed 5 Oct 2021
52. The Washington Post. Derecho: behind Washington, D.C.'s destructive thunderstorm outbreak, June 29, 2012, https://www.washingtonpost.com/blogs/capital-weather-gang/post/derecho-behind-washington-dcs-destructive-thunderstorm-outbreak-june-29-2012/2012/06/30/gJQA22O7DW_blog.html. Accessed 5 Oct 2021
53. National Oceanic and Atmospheric Administration. The derecho of June 29, 2012, <https://www.weather.gov/lwx/20120629svrx>. Accessed 5 Oct 2021
54. National Oceanic and Atmospheric Administration. Service assessment: the historic derecho of 29 June 2012. <https://www.weather.gov/media/publications/assessments/derecho12.pdf>. Accessed 5 Oct 2021
55. U.S. Department of Energy (2012) A review of power outages and restoration following the June 2012 Derecho. U.S. Department of Energy, Washington
56. Sheppy M, Pless S, Kung F (2014) Healthcare energy end-use monitoring. National Renewable Energy Laboratory, Golden
57. Clean Coalition. How a standardized value of resilience will proliferate community microgrids. <https://clean-coalition.org/news/value-of-resilience-to-proliferate-community-microgrids/>. Accessed 7 Oct 2021
58. Eversource. About Eversource. <https://www.eversource.com/content/nh/about/about-us>. Accessed 7 Oct 2021
59. OpenEI. Greater Boston General Service G-2 (B2). https://openei.org/apps/IURDB/rate/view/5cd34bf95457a30e7954e9d6#1__Basic_Information. Accessed 7 Oct 2021
60. Sullivan GP, Dean JD, Dixon DR (2007) Top operations and maintenance (O&M) efficiency opportunities at DoD/army sites: a guide for O&M/energy managers and practitioners. Pacific Northwest National Laboratory, Richland
61. Cost Development Subcommittee (2021) PJM manual 15: cost development guidelines revision, vol 38. PJM, Valley Forge
62. SPEER (2015) Case study—comprehensive retrofit improves CHP cost effectiveness. SPEER, Texas
63. Spurr M, Sampson A, Wang J (2014) Assessment of the technical and economic potential for CHP in Minnesota. Minnesota Department of Commerce, Division of Energy Resources, Saint Paul

64. FSEC Energy Research Center. Types of PV systems. <https://energyresearch.ucf.edu/consumer/solar-technologies/solar-electricity-basics/types-of-pv-systems/>. Accessed 11 Oct 2021
65. NREL. PVWatts calculator. <https://pvwatts.nrel.gov/>. Accessed 11 Oct 2021
66. Jordan DC, Kurtz SR, VanSant K, Newmiller J (2016) Compendium of photovoltaic degradation rates. *Progr Photovoltaics* 24(7):978–989 [[Crossref](#)]
67. Pascual J, Martinez-Moreno F, García M, Marcos J, Marroyo L, Lorenzo E (2021) Long-term degradation rate of crystalline silicon PV modules at commercial PV plants: An 82-MWp assessment over 10 years. *Progr Photovoltaics*. <https://doi.org/10.1002/pip.3456> [[Crossref](#)]
68. Impact of weighted average cost of capital, capital expenditure, and other parameters on future utility-scale PV levelised cost of electricity. In: *Progress in photovoltaics research and applications 2019*, p 28. <https://doi.org/10.1002/pip.3189>
69. Schleifer AH, Murphy CA, Cole WJ, Denholm PL (2021) The evolving energy and capacity values of utility-scale PV-plus-battery hybrid system architectures. *Adv Appl Energy* 2:100015 [[Crossref](#)]
70. European Commission. Data sources and calculation methods, <https://ec.europa.eu/jrc/en/PVGIS/docs/methods>. Accessed 11 Oct 2021
71. IRENA (2017) IRENA cost and competitiveness indicators: rooftop solar PV. International Renewable Energy Agency, Abu Dhabi
72. Kimura K (2019) Current status and future outlook. Renewable Energy Institute, Fukushima
73. Okunlola A, Jacobs A, Ntuli N, Fourie N, Nagel L, Helgenberge S (2019) Consumer savings through solar PV self-consumption in South Africa: assessing the co-benefits of decarbonising the power sector. Institute for Advanced Sustainability Studies, Potsdam
74. Norris BL, Gruenhagen PM, Grace RC, Yuen PY, Perez R, Rábago KR (2015) Maine distributed solar valuation study. Maine Public Utilities Commission, Hallowell
75. Walker A, Desai J, Qusaibaty A (2020) Life-cycle cost and optimization of PV systems based on power duration curve with variable performance ratio and availability. National Renewable Energy Laboratory, Golden, CO

76. Wilcox S (2012) National solar radiation database 1991–2010 update: user’s manual. National Renewable Energy Laboratory, Colorado
77. NREL. PVWatts[®] Calculator, <https://pvwatts.nrel.gov/pvwatts.php>. Accessed 13 Oct 2021
78. U.S. Department of Energy (2013) Grid energy storage. U.S. Department of Energy, Washington
79. Ouramdane O, Elbouchikhi E, Amirat Y, Sedgh-Gooya E (2021) Optimal sizing and energy management of microgrids with vehicle-to-grid technology: a critical review and future trends. *Energies* 14:4166 [[Crossref](#)]
80. Dobkin B, Hamburger J (2014) Analog circuit design, vol 3, 1st edn. Newnes, Oxford
81. Victron Energy B.V. (2016) Lithium iron phosphate (LiFePO₄) battery. Victron Energy B.V., Almere
82. Keyser MA, Pesaran A, Oweis S, Chagnon G, Ashtiani C (1999) Thermal evaluation and performance of high-power lithium-ion cells. Reprint. National Renewable Energy Laboratory, Golden
83. Centolella P, Farber-DeAnda M, Greening LA, Kim T, Estimates of the value of uninterrupted service for The Mid-West independent system operator, p 4. Google Scholar
84. Bustos C, Watts D (2016) Novel methodology for microgrids in isolated communities: electricity cost-coverage trade-off with 3 stage technology mix, dispatch & configuration optimizations. *Appl Energy* 195:204–221 Google Scholar
85. Sullivan MJ, Schellenberg J, Blundell M (2015) Updated value of service reliability estimates for electric utility customers in the United States, Tech. Report, Lawrence Berkeley National Laboratory
86. Office of Energy Efficiency & Renewable Energy. Massachusetts General Hospital Gray Building, Healthcare Energy. <https://www.energy.gov/eere/buildings/healthcare-energy-massachusetts-general-hospital-gray-building>. Accessed 20 Oct 2021

A Multilayer Resilience Assessment of Power Distribution Systems with Reliability Models, Service Restoration, and Dynamic Bayesian Networks

Michel Bessani¹ , Henrique O. Caetano² , N. Luiz Desuó² , Matheus S. S. Fogliatto²  and Carlos D. Maciel³ 

- (1) Department of Electrical Engineering, Universidade Federal de Minas Gerais (UFMG), Belo Horizonte, 31270-901, Brazil
- (2) Department of Electrical and Computer Engineering, University of São Paulo (USP), São Carlos 05508-090, Brazil
- (3) Department of Electrical Engineering, São Paulo State University (Unesp), Guaratinguetá, 12516-410, Brazil

 **Michel Bessani (Corresponding author)**
Email: mbessani@ufmg.br

 **Henrique O. Caetano**
Email: henriquecaetano1@usp.br

✉ **N. Luiz Desuó**

Email: luiz.desuo.neto@usp.br

✉ **Matheus S. S. Fogliatto**

Email: matheusfogliatto@usp.br

✉ **Carlos D. Maciel**

Email: carlos.maciel@unesp.br

Abstract

Electrical energy is fundamental for contemporary society since failures directly impact other critical infrastructures such as water and gas distribution, hospitals, or banking services. Consequently, resilience, which is the capability of a system to handle high-impact low probability events, is a crucial aspect of such systems. Efficient resilience assessment methods are essential to achieving high-performance, resilient energy systems. This chapter introduces a multilayer method to address several factors of power distribution systems' resilience. Reliability regressions model the failures' instant and duration given a weather scenario, a dynamic Bayesian network (DBN) models how probabilities of failure propagate on the system's physical connections, and a service restoration through switching operations, and field crew routing is obtained through an optimization algorithm for a given set of failures. Information related to these factors has the potential to be structured in a layered manner for a better understanding of the dynamic interaction among different information like weather, routes, power grid, and historical events logs. The ability to model these relationships enables the inference of the system resilience for different inputs during analysis. Resilience can also be inferred by considering the uncertainties associated with these layers due to DBN's nature. A case study is presented to show the efficacy of this procedure. The findings showed its ability to

evaluate the resilience of power distribution systems in the face of uncertainty and the considered aspects for different weather scenarios.

Keywords Resilience assessment - Dynamic bayesian networks - Reliability - Service restoration - Power distribution systems

1 Introduction

The reliance on electricity in society is growing at an escalating rate [1]. This dependency is further intensified by the digitalization of existing services and processes and the progress of cyber-physical systems, which integrate cyber components to enhance or provide new functions to physical systems [2]. This interdependence is expected to intensify further in the near future with the advent of Industry 5.0 and Society 5.0 [3]. Furthermore, as stated in the 2023 report of the International Panel on Climate Change (IPCC) [4], there is an anticipated rise in both the frequency and intensity of extreme climate events. Extreme events typically burden Critical Infrastructure (CIs), including water and gas distribution, hospitals, communication, and power systems. This leads to prolonged impairment of these systems, resulting in service interruptions, economic losses, and negative impacts on societal well-being.

Resilience becomes the focal point when examining how CIs react to significant failures on a broad scale and in the face of various threats. It involves the ability of a CI to prepare for, withstand, and recover from significant disruptions. Resilience is linked to the ability to prepare for and adapt to changing conditions and inherently involves a temporal element. This temporal dimension is essential for understanding how CIs can withstand and recover from disruptions, whether deliberate attacks, accidents, or

natural disasters [5]. Therefore, CIs' resilience can be viewed as a dynamic and ongoing characteristic that unfolds over time, encompassing preparedness, response, and recovery efforts to ensure the continuity of essential functions.

The definition of resilience that we adopt is derived from The National Academy of Sciences, Engineering, and Medicine of the United States [6]. According to this definition, resilience is the capacity to effectively prepare for, absorb, recover from, or adapt to current and potential adverse events. Within this framework, it is crucial to emphasize three fundamental components of resilience:

1. Temporal aspect is key for resilience assessment, especially the periods before, during, and after a disruptive event [7];
2. Resilience is scenario dependent, meaning that internal (operational characteristics) and external (attacks or weather variables) factors affect the failure occurrence and response of the system during a disruptive event, and consequently, its resilience [8];
3. Uncertainties will always be presented when assessing the resilience of complex systems. There must be a proper manner to evaluate the performance of a typical power system in the face of different scenarios [9].

Research has mostly focused on the resilience of several critical infrastructures, including water transportation [10], railway networks [11], and others [12]. In the realm of power systems, the ability to operate resiliently is of utmost importance. This is because other important systems and services rely on electricity, making it imperative for power distribution systems (DS) to prioritize resilience. Notably, the bulk of failures occur in power distribution

systems [13]. The research on the resilience of Distribution Systems is interdisciplinary and primarily concentrates on evaluating or improving resilience. DSs resilience assessment can be conducted through various strategies, including historical data analysis, analytical methods, and probabilistic approaches such as stochastic simulation and inference methods.

In addition to considering the advantages and disadvantages of these methodologies, it is important to acknowledge the inherent uncertainty in the resilience analysis of complex systems. These systems, such as power systems and other elaborate engineered systems, often display intricate interdependencies. These complex systems function on multiple levels of knowledge and factors, as will be explained in Sect. 3. As a result, recent research efforts have shifted towards a probabilistic approach, highlighting the importance of systematically considering and evaluating uncertainties in resilience assessment. It is crucial to adopt probabilistic frameworks because they give decision-making power to CI operators and allow for the use of advanced probabilistic methodologies to improve our understanding of the resilience of complex systems. Consequently, this facilitates the implementation of more efficient measures to reduce the impact of risks [9], thereby promoting enhanced ability to recover from adverse events in different essential areas.

The uncertainties related to the resilience of DS can arise from various causes. High-impact, low-probability (HILP) events, such as storms, typhoons, earthquakes, floods, fires, droughts, and heatwaves, are external influences on the system. The uncertainty lies in their incidence, length, and intensities. These incidents have an impact on the DSs as well as other urban infrastructures. Furthermore, distinct operational uncertainties in the DSs are associated with the intermittent nature of demand and generation, the occurrence of failures, the ability to restore

service, the availability of field crews, and the duration of repairs. These uncertainties are internal factors.

Numerous studies in the literature have addressed the issue of evaluating resilience using a probabilistic approach. The study conducted in [14] examines the assessment of uncertain factors using the Graphical Evaluation and Review Technique. Meanwhile, the authors in [15] utilize a Markov Process to evaluate the failure and repair process of CIs. The study conducted by Chang et al. [16] applies random multi-hazards and considers a stochastic recovery process to evaluate temporal resilience. The study conducted by [17] evaluated the resilience of DSs using a Monte Carlo simulation. This simulation incorporated reliability models that considered both failure and repair processes, which were, in turn, affected by weather conditions. In the article [18], a novel approach based on dynamic Bayesian Networks was introduced to model and evaluate the resilience of DSs.

The studies exploiting power system resilience as a multi-layered model have been developed in the context of analyzing the resilience of modern power systems. The resilience of power systems is a complex and multifaceted concept involving various interconnected factors. For instance, a study on the resilience of modern power systems from a complex network perspective investigates the modeling, evaluation, and enhancement of structural resilience in power systems based on a complex network framework [19]. Additionally, a multi-layered Directed Acyclic Graph (DAG) model has been used for resilience formulation in the context of bulk power systems, emphasizing the interconnected layers of the system [20]. Furthermore, quantifying resilience as a key performance indicator is important for power systems, and it involves analyzing existing power systems and identifying resilience improvements in future power systems [21]. These examples demonstrate the application of a multi-layered

approach in understanding and enhancing the resilience of power systems.

This chapter introduces a multilayer resilience assessment approach that utilizes a dynamic Bayesian Network (DBN) to model the components' failures and repair events. Evidence propagation is employed to facilitate the resilience assessment process. In addition, the resilience evaluation takes into account the following external and internal factors: (i) Weather conditions that impact the frequency of breakdowns and the time taken for repairs; (ii) The frequency of failures, which is influenced by the likelihood of component failure and is directly influenced by weather conditions; (iii) The process of restoring service, which aims to minimize the impact of failures on the system's performance through switching operations; and (iv) The actions taken by field crews to mitigate the effects of failures, such as using manual switches to improve service restoration and repairing the failed components.

The relation between these factors and their impact on the DS components is depicted in a layered framework. This schema enables the inference of the system's resilience from various scenario inputs by modeling the interaction between these elements and the system's components during the resilience assessment.

Furthermore, the DBN inherently represents the ambiguity that arises during evaluating resilience. The subsequent portion of this chapter is structured in the following manner: Sect. 2 explains the basic principles of DBN. Section 3 outlines the multilayer resilience assessment approach and how it arranges the models and algorithms for the various factors, then presents the reliability models for failure occurrence instant and duration, the service restoration algorithm, and the resilience assessment through DBN. Section 4 demonstrates the application of

the multilayer approach in a case study. Finally, Sect. 5 provides the concluding remarks for this chapter.

2 Dinamic Bayesian Networks

Bayesian Networks (BNs) are a valuable tool for knowledge representation, particularly when dealing with complex systems [22]. A BN is essentially built upon a Directed Acyclic Graph (DAG), wherein each node in the graph represents a random variable. The edges, depicted as arrows connecting these nodes, signify the statistical dependencies between these variables. These arrows point from parent nodes to child nodes, establishing the flow of influence within the network. Nodes that lack any incoming arrows are referred to as root nodes and are assigned marginal probabilities. For the remaining nodes, conditional probabilities come into play. These probabilities capture the likelihood of each child node's value, considering the values of all its parent nodes, and are stored in a Conditional Probability Table (CPT). In essence, a Bayesian Network acts as a structured framework to map out relationships, dependencies, and probabilities, facilitating a deeper understanding of complex systems [22].

In a BN, nodes correspond to random variables, each with assigned probabilities representing possible states conditioned on their parent nodes. Evidence propagation is an important technique for exploring BNs' inference capabilities for assigning probabilities to nodes under specific conditions. In the context of BNs, assigning a specific value to a node as evidence (denoted as "e") differs from incorporating a new set of observations (denoted as "E") in terms of their scope and impact on the network. When referring to a new set of observations (E), it implies a collection of observed values, i.e., a random sample of the random variables modeled by the BN. These observations

are then used to update the probabilities of other nodes through Bayesian inference, influencing the entire network.

Conversely, when we assign a specific value as evidence (e) to a particular node, we take a more focused approach. This involves fixing the value of a specific node in the network and asserting the truth or occurrence of the observed evidence. This localized evidence assignment indirectly affects the probabilities of other nodes in the network through their dependencies on the evidence node.

To further illustrate the presented concepts, Fig. 1a depicts a typical BN, adapted from an example in [23]. This BN consists of four nodes: Cloudy, Sprinkler, Rain, and Wet Grass. Essentially, the weather condition (whether it's cloudy or not) influences not only the presence of Rain but also whether the Sprinkler is on or off. Moreover, both the Sprinkler being on and the presence of rain impact whether the grass is wet. The process of defining the BN's structure, including its nodes and edges, encodes the presence or absence of dependencies between the variables (nodes), while the CPTs precisely define the strength of these dependencies.

On the other hand, Fig. 1 demonstrates how the process of evidence propagation affects the BN. Initially, a subset of nodes is selected to apply the evidence (in this case, only the node Wet Grass). The process involves setting each node with evidence to a specific state. In our example, the Wet Grass node is set to "True" and we aim to understand how this evidence will impact the probabilities of other nodes. While the BN's structure remains unchanged, the CPTs must be recalculated (represented by question marks in the figure) for all nodes except the one where the evidence is being evaluated (Fig. 1).

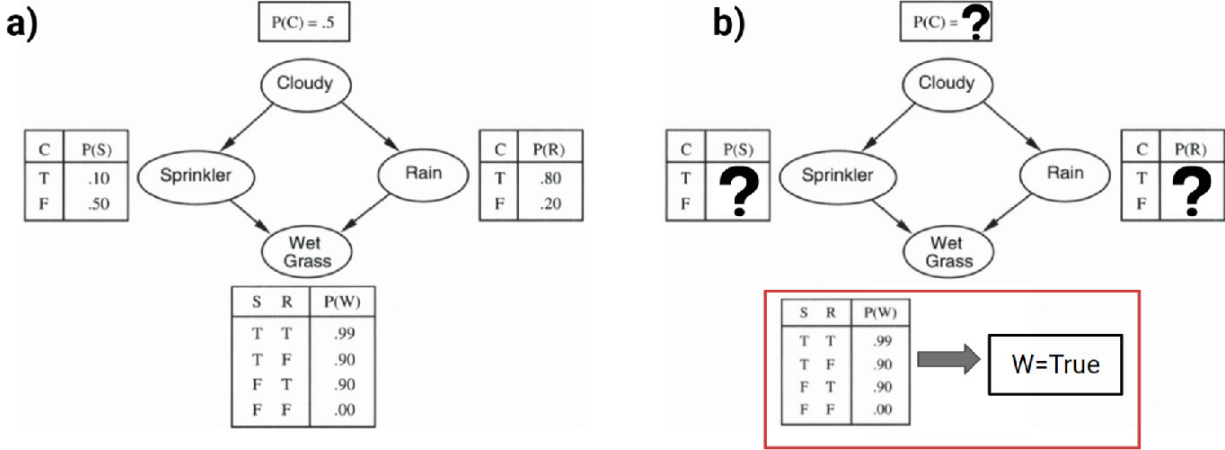


Fig. 1 This example demonstrates a typical Bayesian Network, as shown in (a), with its structure (nodes and edges) and CPTs. In b, node “Wet Grass” is fixed in a given state, and all other probabilities must be updated accordingly

DBNs are an extension of BNs, where the temporal aspect is added. The DBN is considered over a given time window consisting of T time instants, where for each time slice t ($t = 0, \dots, T$), there exists a DAG $\mathbb{G}_t = (V_t, E_t)$, where V_t is the set of nodes and E_t is the set of edges. Finally, for $t = 1, \dots, T$, there is a set $E_{t-1,t}$ of transition edges, which make the connection between V_{t-1} and V_t . Let $\mathbb{G} = \{\mathbb{G}_0, \dots, \mathbb{G}_T\}$, and P be the set of CPTs defined for each node, then the set $(\mathbb{G}, P)$ forms a Dynamic Bayesian Network [24]. A DBN allows keeping the mentioned advantages of BNs, while also adding the temporal aspect by considering the random variables over a set of discrete time slices, with a static BN for each one [22]. In this manner, the edges connecting elements in a DBN can be divided into two types:

1. Intratemporal edges: edges that connect nodes in the same time slice;
2. Intertemporal edges: edges that connect the same or distinct nodes in different time slices.

To delve deeper into the distinctive features of DBNs compared to static BNs, Fig. 2 illustrates a prototypical

DBN comprising three nodes (A, B, and C) across three temporal slices ($t \in \{0, 1, 2\}$). In this depiction, intertemporal edges are highlighted in green, signifying dependencies across different time points, while intratemporal edges are depicted in yellow. It is noteworthy that intratemporal edges may connect the same node across different time slices, as exemplified by the connection between nodes A_0 and A_1 , or between distinct nodes, as seen between nodes C_0 and B_1 . Notably, while the set of intratemporal edges typically remains constant across time slices [22], CPTs may vary for the same node across different time points. For instance, the CPT for nodes A_0 and A_1 could differ, reflecting temporal changes in node probabilities. This dual mechanism enables DBNs to capture temporal dynamics: firstly, by modeling the interactions between nodes across time slices via intratemporal edges, and secondly, by adjusting CPTs over time to encapsulate temporal evolution. Additionally, it is crucial to emphasize that the process of evidence propagation seamlessly applies to DBNs without necessitating any additional modifications [22].

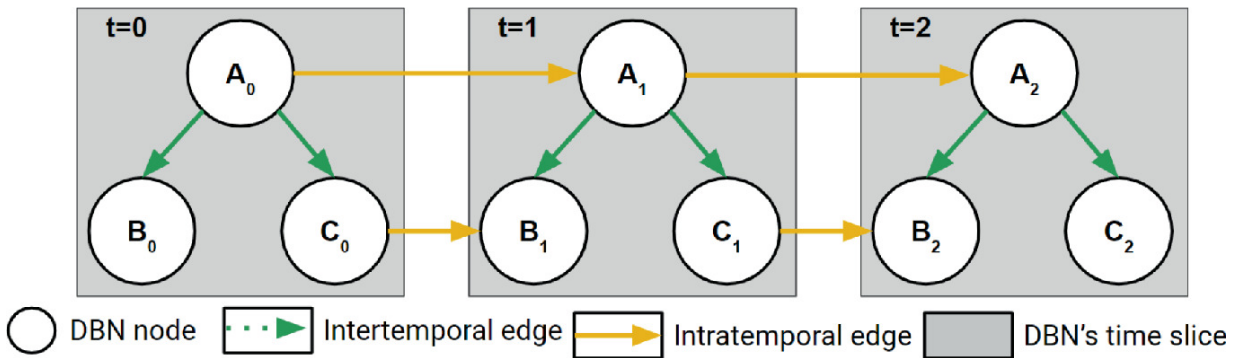


Fig. 2 This example demonstrates a typical Dynamic Bayesian Network, with its structure (nodes and edges) and CPTs. Each time slice represents static nodes for a particular time, and edges between time slices represent the temporal dependence between variables

3 Multilayer Resilience Assessment

This Section discusses the proposed multilayer resilience assessment approach. Firstly, the multilayer structure that combines the considered knowledge and factors, the DBN and Failure duration and occurrence models, and the algorithms to perform evidence propagation, service restoration, and resilience estimation is described in Sect. 3.1. Then, the information, models, and algorithms for the considered factors are presented. Respectively, failures occurrence and duration reliability models that reflect the effect of weather scenarios on failures and repair probabilities in Sect. 3.2, service restoration through manual switches operation and field teams routing in Sect. 3.3, and the resilience assessment using DBN in Sect. 3.4.

3.1 Multilayer Arrangement

The multilayer arrangement of the factors, knowledge, models, and algorithms is depicted in Fig. 3. The black boxes describe the knowledge necessary to execute our approach, which is the data of the DS used to define the DBN structure and to execute service restoration, and the historical data of failures for such DS used to learn the failure occurrence and duration models. The weather scenario gray box is the input used to probabilistically assess the resilience. A given weather scenario results in a failure scenario where service restoration and evidence propagation are executed to allow resilience estimation through MAP performance inference. The white boxes are the models learned from data: the DBN structure learned from the DS data, and the DBN CPTs based on the failure occurrence and duration models which are also influenced by the given weather scenario. The ellipses represent the algorithms used to process the failure scenario sampled from the DBN CPT, and the circle is the resilience estimation based on the MAP performance inference.

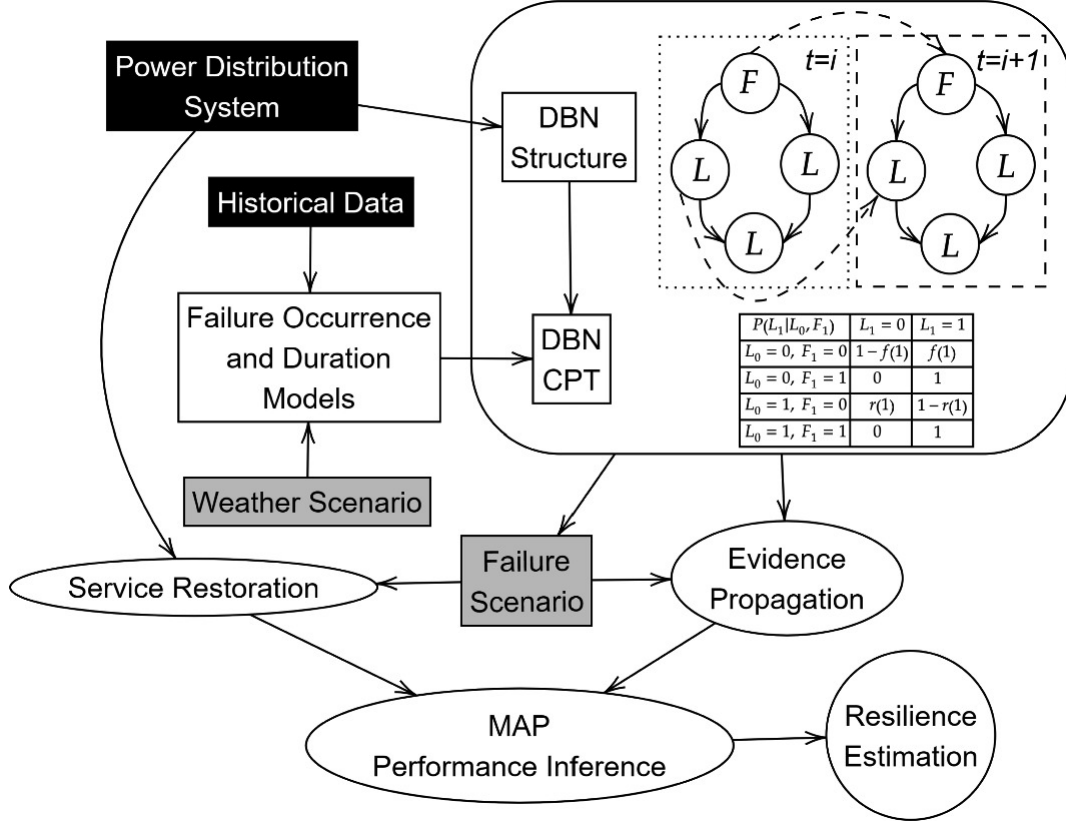


Fig. 3 Multilayer structure that combines knowledge and factors on learned models and runs algorithms to process a given weather scenario and perform resilience estimation

3.2 Failures Occurrence and Duration Models

The power system is divided into three subsystems: Generation, Transmission, and Distribution. Generation is the part of the system responsible for generating electricity. Several generation methods exist, such as thermal power plants, hydroelectric plants, wind and solar panel farms, and nuclear plants. Generation failures generally occur due to equipment failures or operational errors. However, especially in renewable sources, it is not uncommon for operations to be suspended due to a lack of the base resource, with an empty water reservoir in hydroelectric plants.

Transmission is the part that connects generation to distribution systems. If, on the one hand, generating sources such as thermoelectric plants are generally located

close to large urban zones, renewable sources are generally further away. Considering this, the structure of the transmission system varies greatly. The function of transmission systems is to transport electricity under conditions that avoid losses as much as possible. To transport electricity in these conditions, the structure and equipment of the transmission networks are robust. Another point is that as they are not located within large urban zones, their contact with human elements and nature is much less, reducing the risk of accidents that could damage part of the system and generate failures. However, when these disruptive events occur, the impact is significantly large, with large areas becoming de-energized.

Distribution is the system's last part and is responsible for transporting electricity and lowering the electrical quantities to ideal values for use by end consumers. It is the part that has the most number of equipment, and its structure is located within urban areas. Therefore, it is the power system part most subject to failures, which can be operational, such as equipment defects, and related to external factors, such as accidents with vehicles, animals, vegetation, or events related to atmospheric events, such as wind, lightning, and rain.

Failures are an inevitable problem in Power Systems. Any interruption in the electricity supply is considered a failure. A large part of their structure is located in open places and exposed to the environment, which ends up facilitating the occurrence of accidents. Accidents involving vehicles crashing into parts of the system, vegetation touching or falling on equipment, and atmospheric events that cause damage to various parts of the network are examples [25–28] of uncertainty factors that generate failures in the electrical system.

Due to the direct impact on end consumers, such as commerce, industry, and the general population, distribution networks are currently the area with the most

significant emphasis in academic studies. Investigating improvements in the areas of system operation and planning, such as finding the best system configuration and the best positioning for protective equipment, as well as understanding the problems faced by calculating reliability indices, and identifying the most serious threats, are some of the examples of study areas in distribution systems [29–31].

The most common way to evaluate a Power System's behavior during failures is through reliability indices [2, 32–34], calculated with the quantity or duration of failures experienced by a distribution system and the number of customers served by this system. The System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) were the usual metrics to measure the failure impacts on power systems. According to local legislation in each region, system administrators are subject to fines depending on the values of these metrics. Equations 1 and 2 show how SAIFI and SAIDI are calculated.

$$SAIFI = \frac{\text{Total Number of Interruptions}}{\text{Number of Customers}} \quad (1)$$

$$SAIDI = \frac{\text{Total Duration of Interruptions}}{\text{Number of Customers}} \quad (2)$$

Although weather events are not the most common cause of failures, their impact is considerable on the duration of these disruptive events and the number of customers affected. Extreme atmospheric events, such as storms, can result in regions without electricity for days or weeks. Furthermore, they influence other types of problems, such as increasing the rate of accidents involving network components. Therefore, understanding the most harmful events, by modeling how they affect failures' occurrence and duration, is necessary to plan proactive and reactive

measures to reduce the damage caused by them, and is a currently highlighted area of study [35–38].

Regressions are a statistical technique that helps model events of interest. Furthermore, it helps identify and measure the aspects that influence these events. Failures in Electrical Power Distribution Systems can be modeled as the event of interest in Regression models. Factors such as network characteristics and weather events can be included as covariates to check their influence on the occurrence of failures. Generalized Linear Models are a generalization of conventional linear regression and allow for response variables with error distribution models other than the normal distribution, which is a traditional method. It enables the link function that connects a linear model to the response variable and allows the size of the variance of each measurement to be a function of the predicted value.

In [39], this approach was used to model count data to propose a failure rate regression model. The count data is the number of failure occurrences for each day in an observed period. Weather events are included as covariates, using maximum daily values. The included covariates included the number of atmospheric discharges and the maximum occurred wind gust speed. Poisson and Negative Binomial distributions were examined to determine which distribution best fit the failure data. Negative Binomial presented the best result, and the failure rate from the proposed model was defined as in Eq. 3, where nat is the occurred number of atmospheric discharges and the wg is the daily maximum wind gust speed in km/h.

$$\lambda_d = \exp(2.2507716 + 0.0011096nat_i + 0.0274958wg_i) \quad (3)$$

Another option is to model the time as a random variable. The quantity of failures can be measured with the lifetime of the Distribution Systems. Lifetime is when the system operates in its normal state, i.e., without failures, until the

occurrence of a failure event. Similarly, failure (or interruption) durations are another problem that involves time and can be approached by assuming time as a random variable. Survival or Reliability Analysis Regression is a statistical technique that works specifically with problems involving time until the occurrence of an event of interest [40]. Reliability Analysis Regression has three main techniques: non-parametric, parametric, and semi-parametric. For power systems reliability studies, non-parametric and parametric are the most usual choices. Although it has constraints regarding the quality, quantity, and accessibility of data, non-parametric analysis is the technique where fewer assumptions are made, resulting in models closer to the data. For instance, the model cannot provide a probability of the event of interest to occur if the data does not cover the specified time duration. The goal of parametric techniques is to overcome this aspect by offering a more precise model to accommodate any required range. This difference can be observed in Fig. 4, where the Kaplan-Meier estimator (Non-Parametric) and Weibull Distribution (Parametric) reliability curves are compared.

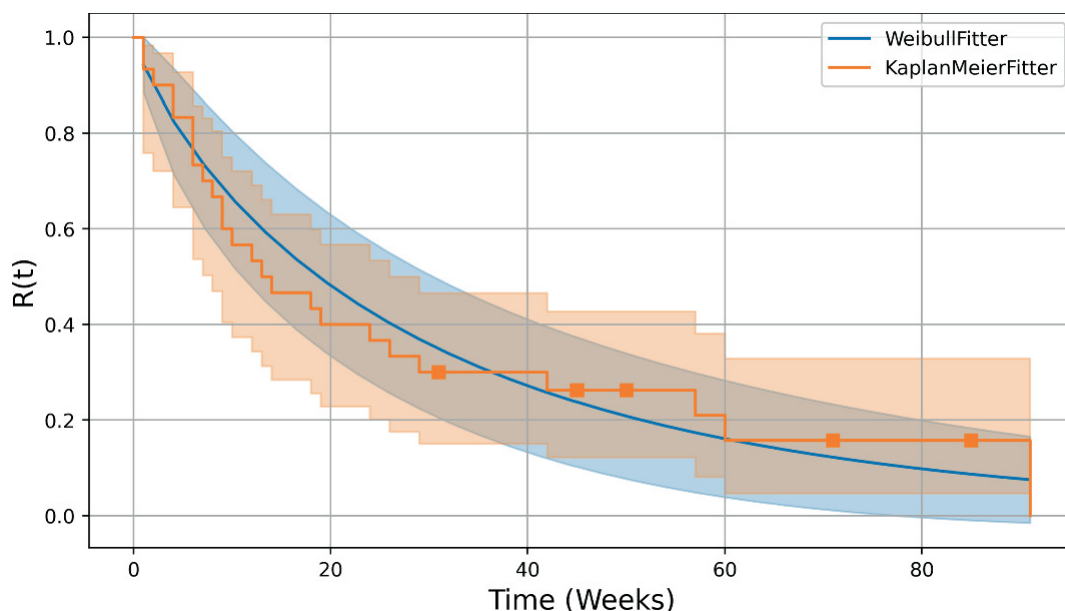


Fig. 4 Reliability Function using Kaplan-Meier Estimator (non-parametric technique) and Weibull distribution (parametric technique) for the same sample of data

Reliability or Survival Function ($R(t)$) is the probability that a subject survives longer than time t . It is the main output to estimate the lifetime or failure duration. Defining Pr as probability, t as time, and T as a random variable denoting the time of occurrence of the event of interest, the reliability function, $R(t)$, can be defined as in Eq. 4:

$$R(t) = Pr(T > t) \quad (4)$$

Lifetime distribution functions (F) is defined in Eq. 5 as the complement of the reliability function $R(t)$:

$$F(t) = Pr(T \leq t) = 1 - R(t) \quad (5)$$

Selecting a probability distribution is crucial for fitting a parametric reliability model. The primary possibilities from the literature, including the Exponential, Weibull, LogNormal, and LogLogistic distributions, will be assessed for building a model for the time to failure and the time to repair, i.e., interruption duration. Equations 6, 7, 8, and 9 present the reliability function for Exponential, Weibull, LogNormal, and LogLogistic distributions respectively.

$$R(t) = \exp\left(\frac{-t}{\lambda}\right), \lambda > 0 \quad (6)$$

$$R(t) = \exp\left(-\left(\frac{t}{\lambda}\right)^\rho\right), \lambda > 0, \rho > 0 \quad (7)$$

$$R(t) = 1 - \Phi\left(\frac{\log(t) - \mu}{\sigma}\right), \sigma > 0 \quad (8)$$

$$R(t) = \left(1 + \left(\frac{t}{\alpha}\right)^\beta\right)^{-1}, \alpha > 0, \beta > 0 \quad (9)$$

Accelerated Failure Time (AFT) modeling is also used to include covariates. Covariates can be considered on the shape and scale parameters of the models. For example, we can model n covariates influencing the Weibull distribution scale parameter λ . The regression for λ will be as in Eq. 10, and the respective reliability function will be as in 11.

$$\lambda(\mathbf{x}) = \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n) \quad (10)$$

$$R(t; \mathbf{x}, y) = \exp \left(- \left(\frac{t}{\lambda(\mathbf{x})} \right)^{\rho(y)} \right) \quad (11)$$

In [41], the non-parametric Reliability Analysis technique called the Kaplan-Meier estimator was used to estimate the outage duration of different groups of interruption durations for a real Power Distribution System. In the mentioned paper, between the failure causes groups Atmospheric, Environmental, Urban, Operational Needs, and Equipment Failure, Atmospheric causes are the factor that leads to more extensive repair time. In [42], a similar result for these groups was found when modeling the lifetime of Distribution Systems.

As the Reliability Analysis Regression technique allows the modeling of the lifetime and failure durations of power systems, a complete reliability framework can be made, allowing, for example, to sample trustworthy times to failure and duration of such failures, which combined with operational aspects of these systems, can be used to calculate reliability indexes, such as SAIFI and SAIDI.

A detailed analysis was made in [43], explaining how to use Reliability Analysis Regression to model failures in Distribution Systems. Statistical criteria were used to determine the best distribution for the interruption duration model. Of the numerical criteria, the Akaike Information Criterion (AIC) and Bayesian Information

Criterion (BIC) stand out. QQ-Plot, a graphical evaluation criterion, is very relevant to decide the best statistical distribution for the proposed model. Failure data from real distribution systems were used to develop such a study.

They found that the LogNormal distribution presented the best result overall. The final equation for the interruption duration for failures in Distribution Systems is shown in Eq. 12.

$$R(t) = 1 - \Phi \left(\frac{\log(t) - 3.9110}{1.7851} \right) \quad (12)$$

They also applied the same approach to model the lifetime of Distribution Systems. Weibull distribution presented the best result. Equation 13 presents the final equation for the lifetime model.

$$R(t) = \exp \left(- \left(\frac{t}{127.8349} \right)^{0.5208} \right) \quad (13)$$

After determining the best statistical distribution for each model, covariates were included to evaluate the impact of each event and how it modifies the number of failures and interruption duration. The tests included maximum daily values for six weather events: number of atmospheric discharges, wind speed, precipitation, maximum and minimum temperature, and relative humidity. The first three showed to be the more relevant for the number of failure events.

In Eqs. 14 and 15, the reliability function for the interruption duration (t_d) and the lifetime (t_l) of Distribution Systems models with weather covariates ($\mathbf{x}$) = $[AD, WS, P, T_{\max}, T_{\min}, RH]$ were presented. AD represents the number of Atmospheric Discharges, WS is Wind Speed, P is precipitation, $T_{\max}$ is for maximum temperature, $T_{\min}$ is for minimum temperature, and RH is for relative humidity. To use the covariates, wind speed is

in kilometers/hour, precipitation is in millimeters, temperature is in Celsius degrees, and relative humidity is in percentual.

$$\begin{aligned}\mu(\mathbf{x}) &= 4.5715 + 0.0001AD + 0.0089WS + 0.0027P - 0.01021T_{\max} \\ &\quad + 0.00636T_{\min} + 0.00125RH\end{aligned}\tag{14}$$

$$R(t_d) = 1 - \Phi\left(\frac{\log(t_d) - \mu(\mathbf{x})}{0.2387}\right)$$

$$\begin{aligned}\lambda(\mathbf{x}) &= 4.9715 - 0.00064AD - 0.0277WS - 0.0035P + 0.0106T_{\max} \\ &\quad - 0.0123T_{\min} - 0.0017RH\end{aligned}\tag{15}$$

$$R(t_l) = \exp\left(-\left(\frac{t_l}{\lambda(\mathbf{x})}\right)^{-0.4031}\right)$$

Another example is shown in Figs. 5 and 6. The reliability curves of failure duration and lifetime models presented in Eq. 14 and 15 are demonstrated, with wind speed and the number of atmospheric discharges, which are two relevant factors for the models, assuming different values and the other covariates were used with their average values. For both cases, when the wind speed is slow and the number of atmospheric discharges is low, the chances of the occurrence of the event of interest are below the median case represented by the baseline curve. For the failure duration, it means that the probability of observing a longer interruption is below the baseline curve. For the lifetime, i.e., time to failure, the probability of observing a longer working time before a failure is above the baseline curve. However, as the combinations of atmospheric events present greater values, the chances of failure duration being longer and the system remaining for less time without a failure occurrence decrease drastically.

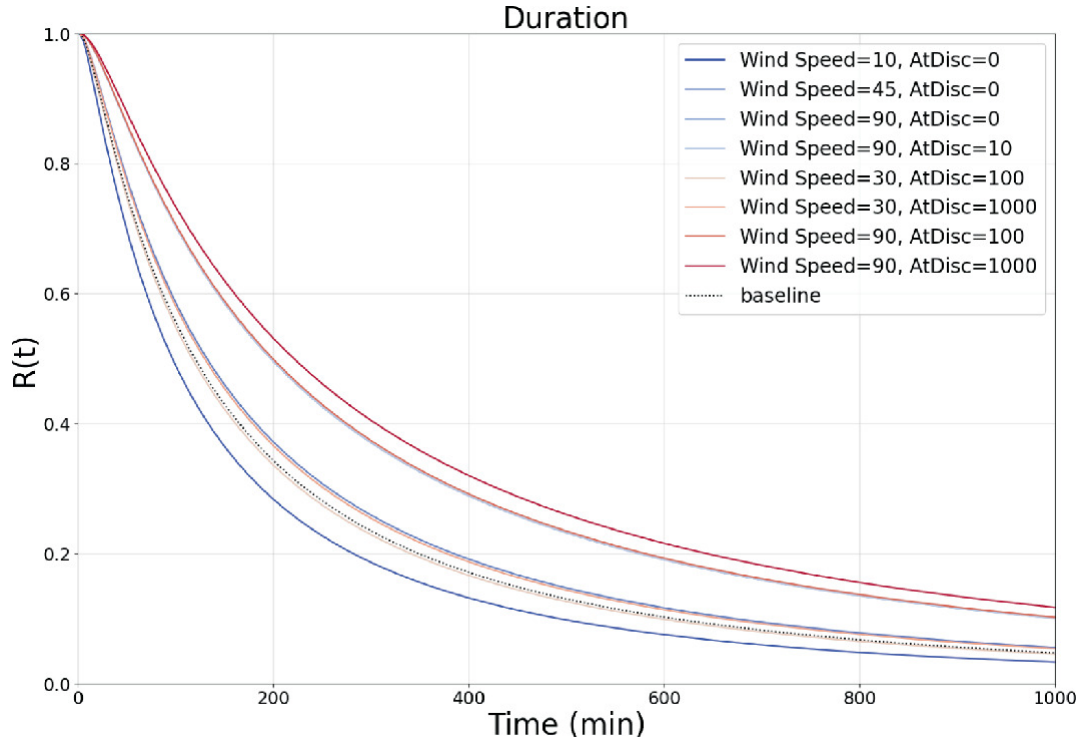


Fig. 5 Failure Duration Model Reliability Curve $R(t_d)$ with weather covariates (Eq. 14). The baseline curve uses the median value from the weather events for the covariates. Wind Speed in kilometers/hour and number of atmospheric discharges are tested with different values

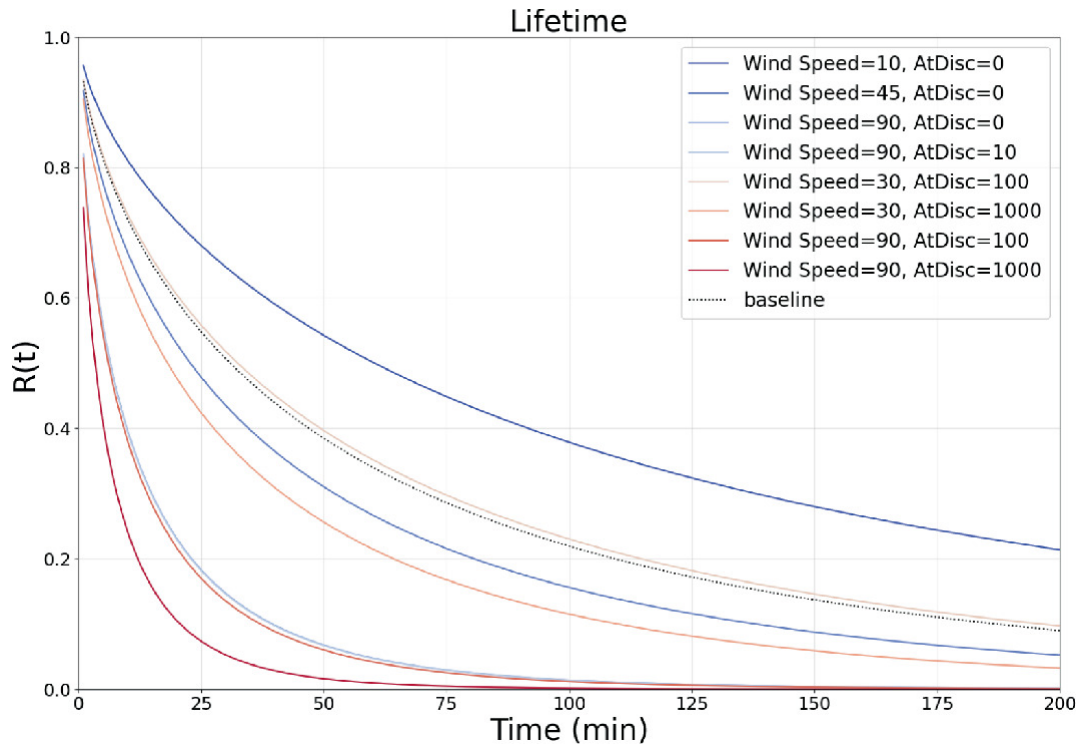


Fig. 6 Lifetime Model Reliability Curve $R(t_l)$ with weather covariates (Eq. 15). The baseline curve uses the median value from the weather events for the covariates. Wind Speed in kilometers/hour and number of atmospheric discharges are tested with different values

Depending on the desired application, the proposed covariates can be maintained or removed, and new ones can be added if new data is available to fit the reliability regression models.

3.3 Service Restoration

The representation of the electric power distribution network is $G_E = \{V_E, E_E\}$, with nodes in V_E connected by edges in E_E . Conventional distribution systems maintain a radial layout, i.e., without cycles. After faults occur, there is the necessity to perform service restoration, which consists of operating the normally open and closed switches to reenergize healthy out-of-service consumers and maintain the system's radiality followed by repairing the faulted components. Such operations are performed by field crews that travel through the road network to operate the switches and perform repairs. These switches divide the electrical system into several sectors, and can also be referred to as node cells [44]. This section presents an approach for routing maintenance teams and obtaining feasible manual switch operations and network reconfiguration during teams' patrols.

3.3.1 Maintenance Teams Routing

Traditionally, the approach to outage management involves delineating the affected area by cross-referencing data from multiple sources after a system failure and activating protective measures [45]. Subsequently, distribution system operators utilize remotely controlled switches to narrow down the affected area before deploying repair teams to inspect nearby power distribution lines for damage and ensure safety before re-energization [46]. This

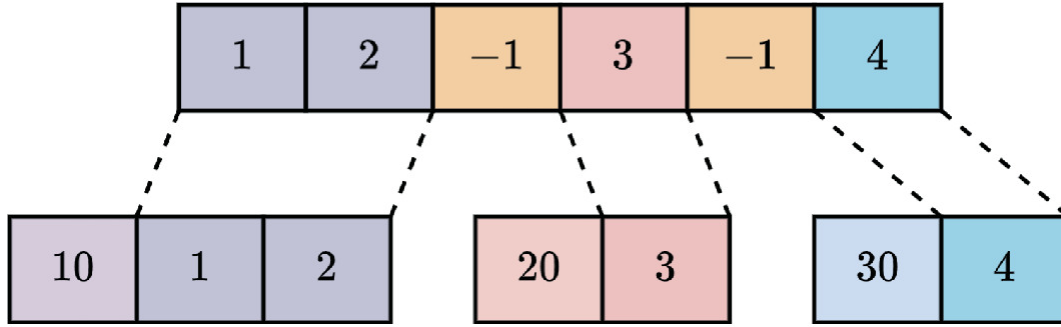
process necessitates a thorough inspection of the entire affected zone by maintenance crews. Consequently, the patrol method can be viewed as a routing challenge, wherein, in the worst-case scenario, the fault remains undetected, leading crews to inspect the entire affected area.

The displacement of the maintenance teams may be impacted by the state of the road network. Using the notation $G_R = \{V_R, E_R, w_R\}$, the road network can be represented as a directed weighted graph. It has nodes in V_R that represent geographic locations, edges in E_R that represent directed roadways connecting these nodes, and a weight function $w_R : V_R \times V_R \rightarrow \mathbb{R}_{\geq 0}$ that assigns distance values to edges to facilitate transportation and logistical analyses. For instance, there are various reasons why traffic speeds can vary. The weather, the day of the week, the time of day, and unplanned events are just a few of the many factors that affect traffic flow, according to [47]. Thus, it is crucial to include external environmental information to reduce prediction errors. The study of predicting traffic flow in unforeseen circumstances, such as the absence of real-world data, accidents, and congestion, as well as the applications of integrated models to traffic forecasting are of great interest to the scientific community [48]. Moreover, simulation frameworks can be used to quantify the traffic speed effect on power distribution systems' reliability indices [49].

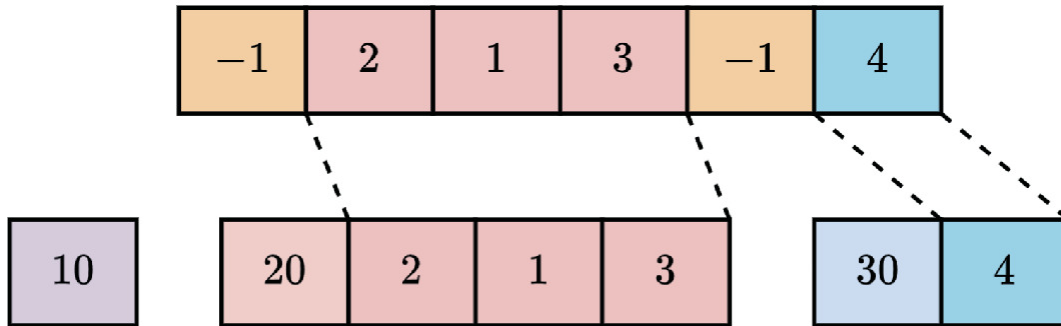
To perform routing of maintenance teams, we can express a set of nodes $P \subseteq V_G$ that represents the sites to be investigated. First, the power distribution system must be projected towards the road network. This step requires geoprocessing and graph theory techniques. One technique to carry out this projection is to assign each node of the electricity distribution system to the nearest road network node. Another technique involves adhering each electrical

node's projection to the nearest edge of the road network by splitting it into two new edges. Before being dispatched to address failure occurrences, maintenance teams must already be displacing, carrying out repairs, or performing some other routine tasks, as opposed to beginning in depots or operational bases as in usual routing problems.

A broader approach involves initiating the patrolling process for the available crews set M at nodes $s = \{s_m : s_m \in V_G\}_{m \in M}$ rather than at operational bases. To utilize this alternative method, specifying all s_m as the operational base location is acceptable. Another relevant element is the delay component τ_m , which signifies the time when the m th team completes its previous task and commences patrolling, denoted by $\tau = \{\tau_m\}_{m \in M}$. Figure 7a illustrates an appropriate encoding for the patrolling problem and a permutation operator applicable to such representation, for a Genetic Algorithm (GA). In this illustration, the -1 element divides the itineraries of the three available maintenance teams. The nodes to be inspected are labeled as $P = \{1, 2, 3, 4\}$. In addition, teams 1, 2, and 3 begin patrols at different points $s = \{10, 20, 30\}$. Permutations of such an array, e.g. Figure 7b, should be used in this situation by the optimization method. By performing permutations, the order of the nodes and the team assigned to the node change. The path to travel from one point to another through the road network graph is obtained through Dijkstra's algorithm.



(a) Example.



(b) Permutation.

Fig. 7 Illustration of the encoding schema used to perform maintenance teams routing. Three teams are stationed at the starting locations $s = \{10, 20, 30\}$ in this illustration of the patrol solution. Points for inspection are $P = \{1, 2, 3, 4\}$. In Fig. 7a, the first team's route begins from position 10, followed by positions 1 and 2, respectively. Simultaneously, the second team travels from position 20, which is its initial position, to position 3. Traveling from 30 to 4 is the third team journey. These patrolling are accomplished simultaneously by the three available teams. There is a permutation of this case in Fig. 7b where the second team moves from point 20 to 2, then 1 and 3, while the first team stays in place. The same route is used by the third team

The element -1 serves as a marker to partition the inspection points for each crew. Through permutation, this approach allows teams to interchange their patrolling regions. Such solution encoding aids in determining the optimal number of teams from the available ones, as some teams may remain inactive. Figure 8 illustrates a restoration scenario where only two of four potential teams were deployed.

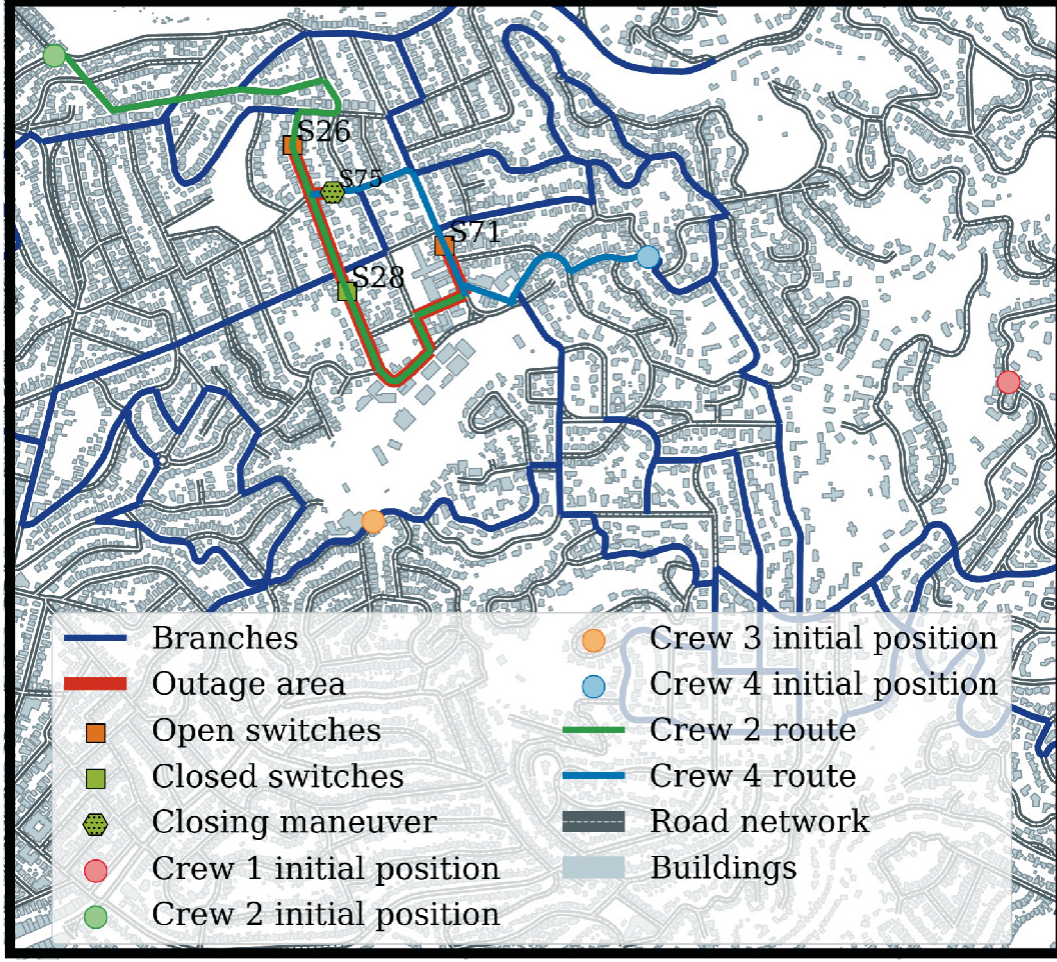


Fig. 8 This example involves a restoration process of a surrogate distribution system having an outage area of 1.18 km and two sectors. Initially, there were 391 out-of-service customers isolated from the remainder of the system by manually operated switches S26, S71, and S75. In addition, there were four available crews. The representation of the patrolling procedure shows the route for teams 2 and 4. These routes comprise their journey and outage area patrolling, chiefly performed by team 2. Finally, while inspecting, team 4 handles S75 closing and restores out-of-service customers in 0.23 h. During the entire process, teams 1 and 3 remain inactive

Different characteristics, like the distance of the network's edges, $w_G(i, j)$, are incorporated in the edge weight function $\psi : V_G \times V_G \rightarrow \mathbb{R}_{\geq 0}$, which is specified in Equation (16). Two velocity levels are recognized in this context, v_p and v_d . In particular, when examining a node that is part of the set of necessary nodes in P , v_p is chosen, and v_d is the velocity related to dislocation speed between road network nodes until arriving at another node in P .

Additionally, the function $t_v : V_G \rightarrow \mathbb{R}_{\geq 0}$ indicates the time required to operate the manual switches necessary to perform power system restoration.

Another aspect incorporated in Eq. (16) is a factor a_j where components with higher change to be experiencing a failure will have their edge weight reduced to be prioritized during the routing solution. The weights of the paths between the road network nodes are modified to prioritize regions with a high estimated likelihood of containing failures through the factor $a_j = 1/(1+\hat{\lambda}_j)$, where $\hat{\lambda}_j$ is an estimated failure rate or failure probability for the i -th component, as discussed in Sect. 3.2. Critical entities such as hospitals, fire departments, information centers, banks, security departments, and industries are accounted for in a critical load factor l_j . As noted in previous works [50, 51], l_j may occasionally integrate another weighting for combining other information sources or priority settings. The χ acts as an indicator function: in the case where $j \in P$, $\chi_P(j) = 1$; in the other case, $\chi_P(j) = 0$.

$$\psi(i, j) = a_j l_j \left[\frac{w_R(i, j)}{(v_p - v_d)\chi_P(j) + v_d} + t_v(j) \right] \quad (16)$$

The routing process's objective function $f(s, \tau, x)$, which should be minimized, is represented by Eq. (17). First, for a given set of routes x , this equation calculates the cost of each crew member's m to travel through the weighted shortest path using the weighting specified in Equation (16). The length of the weighted shortest path between nodes i and j is calculated by the function $\delta(i, j)$ and using the weights calculated in Eq. (16). For the m -th route, $\delta(s_m, x_{m1})$ represents the first portion of the journey from the starting point in $s = \{s_m : m \in M\}$ to the first visiting point described in x . Then, the second and third terms take into consideration the order in which node inspections are performed as well as the amount of time

needed to complete actions like manually operating a switch. Moreover, the optimization process uses the minimax method [52] to identify and minimize the crews' pathways with the maximum cost, i.e., to minimize the worst-case.

$$f(s, \tau, \mathbf{x}) = \max_{m \in M} \left\{ \delta(s_m, x_{m1}) + \sum_{j=1}^{|P_m|-1} \delta(x_{mj}, x_{mj+1}) + \tau_m \right\} \quad (17)$$

3.3.2 Manual Switches Operation and Network Reconfiguration During Patrol

The majority of distribution systems operate in a radial arrangement, which prevents a load node from being connected to a power source (substation or distributed generation) simultaneously through more than one electrical path. Radiality is the constraint that needs to be respected when defining switching operations. During service restoration execution, the network topology is changed by the maneuver of switches (changes from open to closed states and vice-versa) to reconnect healthy out-of-service customers and repaired elements. Since switches are the components responsible for topology changes, they define the minimum level of granularity for network operations. The smallest set of network components that can be isolated from the rest of the distribution system by opening switches or protection devices is called a sector. Figure 9 shows a sector representation.

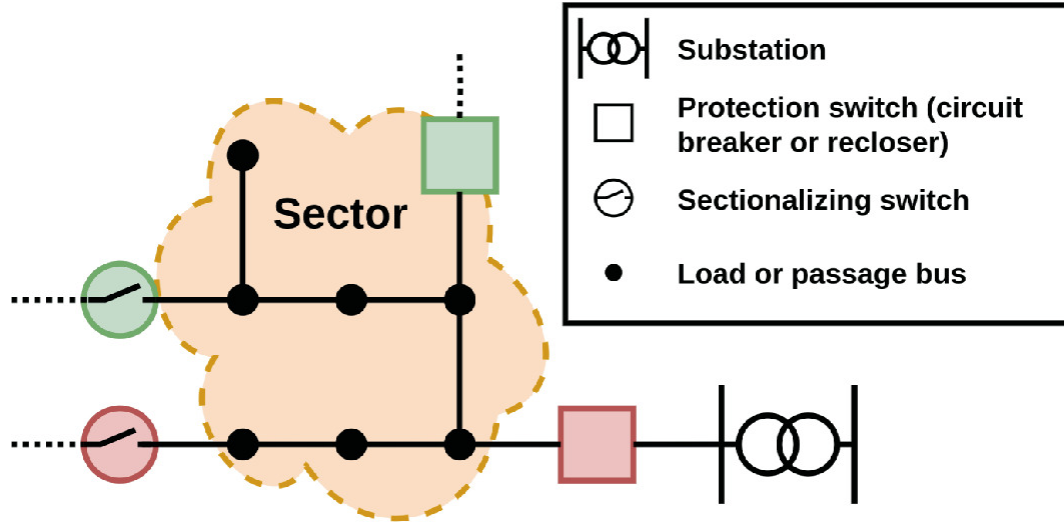
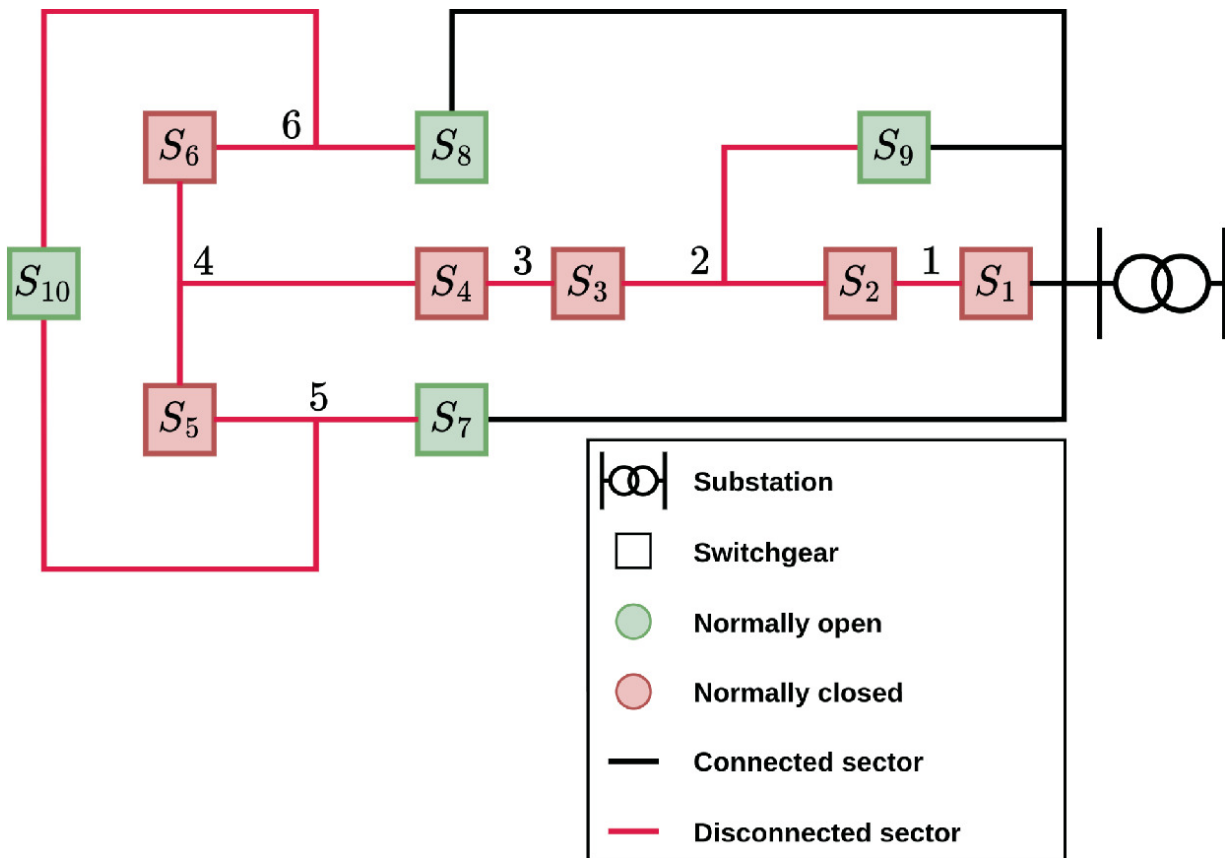


Fig. 9 Illustration of a sector of the distribution system. The set of components that can be isolated from the rest of the distribution system by opening switches or protection devices defines a sector

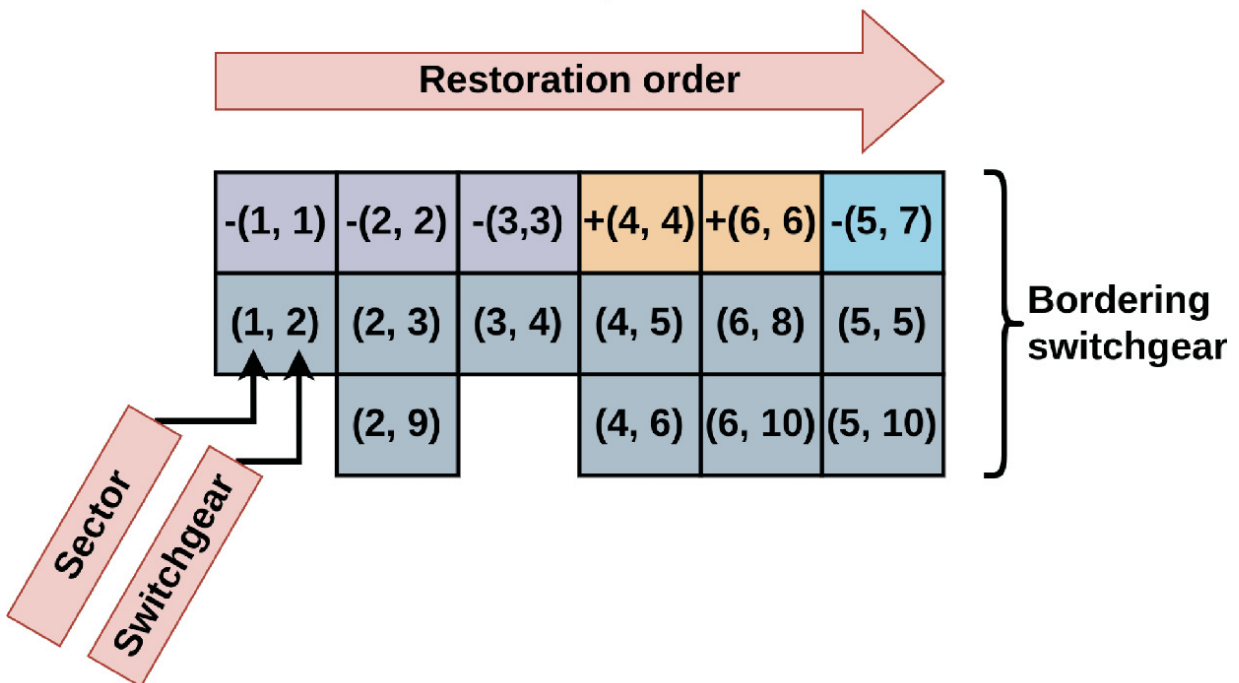
After faults occur, protection devices' action and isolation operations result in disconnected components. These components are divided into sectors, and a candidate restoration solution is encoded in a matrix Y . In essence, each element of Y is a signed pair, and each pair comprises the number of a sector and the number of the switch that must be closed to restore service to this sector y_{ij} . The operation that reenergizes a sector is defined by closing the switch that connects a de-energized sector to an energized one, and these operations are represented as the second value of each signed pair in the first line of the matrix ($y_{1j}, \forall j$). The maintenance teams must patrol the sector and open the other bordering switch before the closing maneuver to address the radiality constraint. These open maneuvers are represented in the next lines of the matrix Y , and each $y_{ij}, \forall i > 1$ indicates the necessary switch open maneuver to restore the j -th sector. In this situation, the sequence of the sectors in this encoding corresponds to the sequence of the restoration procedure.

An advantage of this encoding is that it allows a reduction of the number of maneuvers to restore adjacent sectors by combining the switch operations. This is

achieved by combining the signal of sectors, where adjacent sectors with the same signal compose a super-sector that can be restored through a combination of their open and close switch operations, the open maneuvers of each sector can be skipped due to the need to close the same switch for the restoration of the next sector in the super-sector. Figure 10b depicts an example of a reconfiguration encoding illustrating the number of switch operations by composing super-sectors. Given a feasible reconfiguration to achieve service restoration encoded in $\mathbf{Y}$, the routing optimization algorithm from Sect. 3.3.1 must be executed to guarantee the teams take an optimized route.



(a) System.



(b) Encoding.

Fig. 10 A distribution system with several disconnected sectors, sectionalizing equipment, and a substation is shown in Fig. 10a. The encoding maps out the disconnected area into an array of its sectors. Figure 10b illustrates one possible network reconfiguration solution encoding. Each tuple in the array has two elements: the first is connected to the sector being restored and the second is related to the switch being closed to restore it. The other bordering switches must be open before the closing maneuver to maintain radiality during service restoration. By the signal change, it is possible to combine adjacent sectors into a single restoration stage using this encoding. The example generates three super-sectors and three stages of restoration, the first of which is composed of sectors $\{1, 2, 3\}$. Moreover, the closing switch is S_1 , and the opening switches are S_4 and S_9 . $\{4, 6\}$ is the second super-sector with the closing switch as S_4 , while the opening switches are S_8 , S_5 , and S_{10} . The closing switch is S_7 for the last super-sector, 5, with the opening switches S_5 and S_{10} .

This encoding ensures that one switch will be closed in each restoration phase, however, it does not guarantee practical solutions. Then, depending on the following variables, Equation (18) evaluates the practical feasibility of the solution, and n_o is the number of elements leading to an unfeasible solution.

- o : The solution is impractical.
- p : The switch being closed is a neighbor of nodes supplied with electricity.
- q : The switch being closed must intersect another super-sector already in service or previously restored.
- r : the elements of a super-sector are contiguous in the graph
- s : a closing switch can only be used to restore no more than one super-sector

$$((\neg p) \wedge (\neg q)) \vee (\neg r) \vee (\neg s) : \implies o \quad (18)$$

The objective function to be minimized to obtain a service restoration Y is presented in Eq. (19). For every restoration step $\iota \in I$, where I represents the whole restoration process, the teams' starting positions s_ι and the delays associated with them τ_ι are updated iteratively. Furthermore, the penalty factor ρ is increased by the number of feasibility infractions n_o to account for

violations. In this case, a routing solution is represented by $\mathbf{x}_\iota$, where P_ι is the set of all nodes, including switches, in the super-sector ι . In Sect. 3.3.1, the optimal routing solution is represented by the term $f^*(\cdot)$, which comes from Equation (17). The count of customers that are still out-of-service is then multiplied by this solution. This count is represented by the summation of the customers c_ζ within super-sector ζ during the ι th restoration step.

$$g(\mathbf{Y}) = \sum_{\iota \in I} f^*(\mathbf{s}_\iota, \boldsymbol{\tau}_\iota, \mathbf{x}_\iota) \sum_{\zeta \in I: \zeta \geq \iota} c_\zeta + \rho n_o(\mathbf{Y}) \quad (19)$$

This approach consists of a bi-level optimization procedure, each service restoration candidate solution $\mathbf{Y}$ aims to minimize $g(\mathbf{Y})$, and the teams routing necessary to perform the service restoration are obtained by minimizing the $f(\cdot)$ (Eq. 17). A detailed formulation and discussion of such an approach is presented in [49].

A tournament-based genetic algorithm (GA) was utilized for both levels of optimization. In the lower level, which is the routing mechanism in Sect. 3.3.1, the GA employs ordered crossover (OX1) and swap operators as crossover and mutation, respectively. These operators generate controlled permutations of genes, which are the nodes to be inspected during the patrolling phase. The chromosomes are the routing solutions in this case. In the upper level, the crossover operator is maintained to produce permutations among sectors. However, different mutation operators are used in this stage. The swap operator is employed to exchange the order of the sectors and which switch will energize the sector, in addition to the flip-bit for signal change. In this case, the swap mutation is performed in the horizontal and vertical directions in Fig. 10b. Readers who want more information about these genetic operators should refer to [53]. The GA parameters used to produce the results presented in Sect. 4 are as follows:

- Population size: 300
- Crossover rate: 0.8
- Mutation rate: 0.2
- Tournament size: 3.

3.4 Resilience Assessment Using DBN

To assess the resilience of systems using a DBN, it is necessary to define the DBN structure and conditional probabilities to allow simulation of disruptive events effects through evidence propagation followed by the resilience estimation. These aspects will be detailed in the remainder of this Subsection.

3.4.1 Structure of the DBN

The first step in constructing the DBN for resilience assessment is to obtain its structure. It involves defining the representation of each node within the DBN, and in this method, every node is conceptualized as a component within the topology of a DS. While this approach can be applied to model various CIs, the primary focus here is on power systems. Consequently, each node corresponds to an electrical bus, which can be either a load or a feeder. Denoted as N_t , the set of nodes for the DBN's time slice at time t is established. Figure 11a shows the topology of a typical electrical power system, which is then used to model a DBN's structure, as exemplified in Fig. 11c.

Each node is modeled as a binary variable, offering two possible values: $n_t = 0$ signifies that the n -th node (where $n \in N$) at time t is functioning normally, and $n_t = 1$ indicates that the node is either out of service (de-energized) or in a state of failure. It's essential to emphasize that with this strategy, every component within the energy system will correspond to a dedicated DBN node at each time slice, as exemplified in Fig. 11c. Consequently, the process of assigning a node a specific

value (either 0 or 1) is employed to simulate the occurrence of a specific component failure, as shown in Fig. 11b. This simulation is later utilized in conjunction with evidence propagation to model the probability of disruptive events.

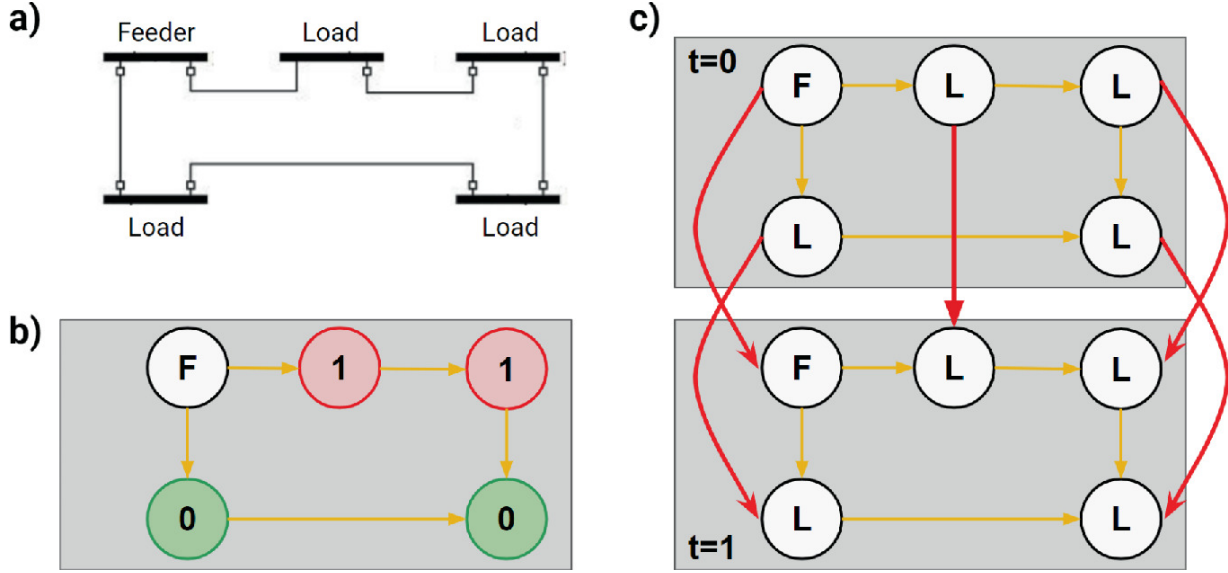


Fig. 11 Procedure to define the DBN's structure based on the energy system's topology. In **a**, the original topology of a modified 5-bus test case is presented. In **b**, the respective static BN is shown, with a typical failure scenario (green nodes working; red nodes in failure). In **c** a DBN with replicated static time slices is modeled (intratemporal edges are yellow, intertemporal are red)

3.4.2 Conditional Probability Tables

After the structure of the DBN is defined, the next step is to model the CPTs that will define the statistical dependencies of each node. To do so, two reliability models are necessary. The model of failure occurrence probability given a time instant ($1 - R(t_l)$) and the model of failure duration probability ($R(t_d)$). Section 3.2 presented and detailed these two models. In this Subsection, we will denote for a given time instant t that $1 - R(t_l = t) = f(t)$ and $R(t_d = t) = r(t)$.

To model the CPTs of all nodes in the DBN, the following rules are applied:

1. All feeders start in normal operational conditions (probability of failure equal to 0 at $t = 0$);
2. If all feeders connected to a given node n at time t are in failure, then the probability of the node being in failure at the same time is equal to 1, which is mathematically modeled as $P(L_t = 1)$;
3. If a load node L has been in failure for the previous k time slices (i.e. $L_{t_i} = 1$ for $t_i \in \{t - 1, t - 2, \dots, t - k\}$) then the probability that such a node goes back to normal operational conditions in the next time slice t is mathematically expressed by $r(t)$;
4. If a load node L has been in normal operational conditions for the previous k time slices (i.e. $L_{t_i} = 0$ for $t_i \in \{t - 1, t - 2, \dots, t - k\}$) then the probability that such a node experiences a failure in the next time slice t is mathematically expressed by $f(t)$.

With the aforementioned rules as a starting point, Fig. 12 shows an example. It is important to highlight that while the Figure shows a simple example with only two nodes (1 feeder and 1 load) with the proposed method, it can model any radial energy system with multiple feeders and loads. Additionally, different topologies (depending on the action of protective devices or islanding mode) can be assessed by this approach, by adapting the final DBN accordingly. This allows the proposed method to be flexible to deal with distributed generation in active Power DSs.

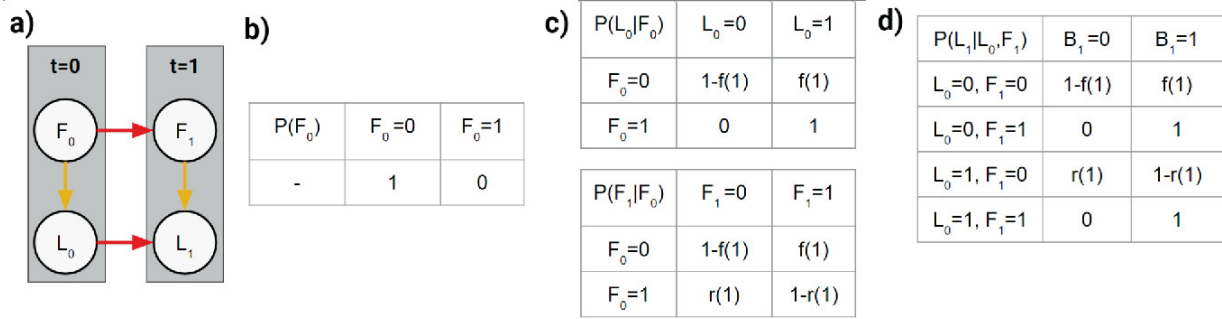


Fig. 12 Example of a simple energy system with a single feeder connecting a single node. In **a**, a DBN's structure with two-time slices is presented. In **b**, we have the CPT for the root node. In **c**, two possible CPTs for a child node, are conditioned to its parent. In **d**, a CPT of a child node with two parents

3.4.3 Simulating Disruptive Events with Evidence Propagation

With the provided tools, we can already model a full DBN, consisting of both its structure (nodes and edges) as well as the conditional probability tables relating different nodes. With this in mind, the next step is to use the process of evidence propagation to properly simulate failure scenarios in a DS. In the proposed approach, each node in the DBN is related to a physical component (in our context, an electrical bus, either a load or a feeder). With this in mind, consider that a disruptive event consists of defining a set of components, i.e., DBN nodes, to be in failure for a specific period. By remembering that each DBN's time slice represents a period in time, and by properly defining the temporal scale (the time that passes between subsequent time slices), the following procedure can be used to define a disruptive event:

1. Consider a set of nodes to be in failure ($N_f \subset N$), each one with an instant of failure (t_f) and a failure duration (t_d);
2. Consider all time slices in the DBN ($t_s \in \{0, \dots, T_h\}$), where T_h is the time horizon, representing the maximum number of time slices;

3. Consider that the state of a given DBN's node (0 for working; 1 for failure) at a given time t_s is represented by $s_{n,t}$;
4. For each node in failure: if $t_f \leq t_s \leq t_r$, the node's state is considered as in failure ($s_{n,t_s} = 1$); otherwise, it is in working state ($s_{n,t_s} = 0$).

To illustrate the procedure, Fig. 13a presents a simple example of a 5-bus energy system with a specific disruptive event. Figure 13b-d depict how the DBN assigns values to its nodes based on the failure scenario. It's noticeable that while a subset of nodes has fixed values (either 1 or 0, depending on the disruptive event), all other nodes (depicted in blue in the figure) don't receive fixed values since they aren't part of the disruptive event. Instead, their Conditional Probability Tables (CPTs) are updated to account for the occurrence of the disruptive event. The process of assigning fixed values to some nodes and updating the probabilities of others is achieved through evidence propagation.

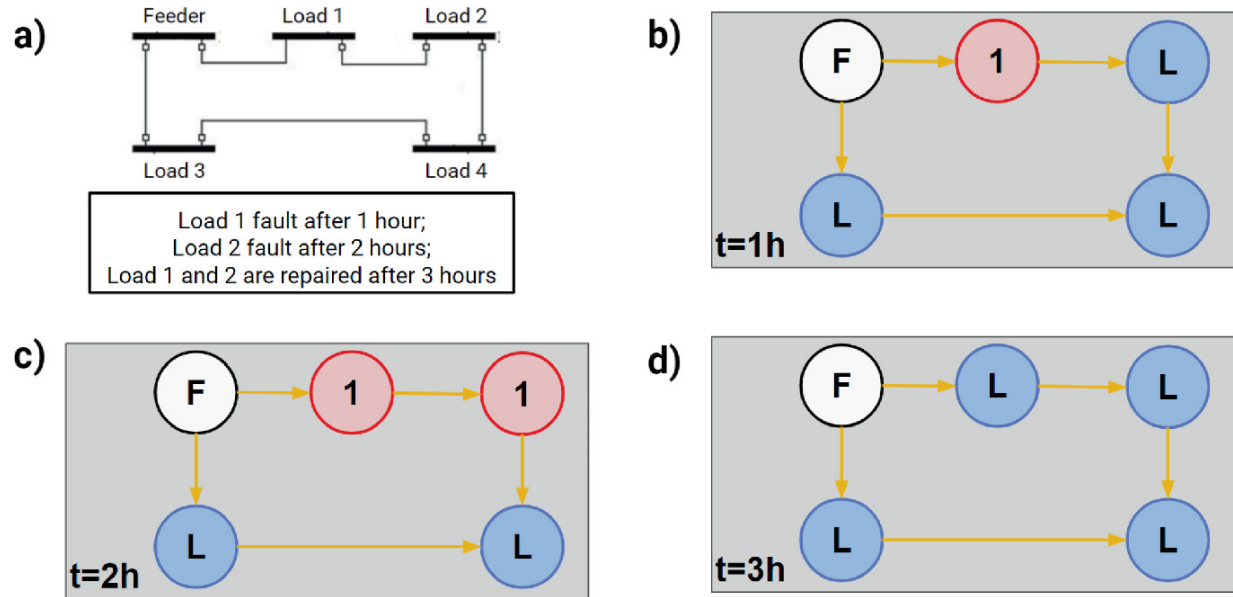


Fig. 13 The possibility of modeling disruptive events by using evidence propagation. In **a**, the 5-bus IEEE test case is presented as a reference, along

with a disruptive event (black box). In **b**, the DBN for $t = 1$ hour is shown, with Load in failure (state equal to 1); in **c**, for $t = 2$ hours, both Load 1 and 2 are in fault; finally, in **d**, after $t = 3$ hours, both loads are repaired. Nodes in red are in failure; nodes in blue have no defined state

3.4.4 Resilience Estimation of a DS

After the evidence propagation to simulate a disruptive event scenario, the DBN with updated probabilities can be used to assess the overall Resilience of the energy system. However, since the DBN deals only with probabilities (which represent how likely a component is to be in failure or working state at a given time slice), it is not possible to directly assess a single resilience curve for the whole time horizon. Instead, two possibilities are possible:

1. It is possible to sample from DBNs given the updated CPTs [23], which can be done to simulate various trials by Monte Carlo approaches, and consequently, generate several resilience estimations;
2. With the updated probabilities, it is possible to find the most likely state of the DBN as a whole (in other words: if a component is working or in failure for each time in the time horizon), which is done by the process called Maximum a Posteriori (MAP) estimation [22].

While the strength of applying Monte Carlo approaches to the process of random sampling in DSs has been highlighted previously in the literature [18], the results presented in this Chapter will apply the MAP technique to calculate the most probable state of each component at a given time. Consequently, it is possible to evaluate the most probable resilience curve, by calculating the performance function for each time. The Supplied Energy (SE) will be used as the performance function, which can be calculated as shown in Eq. 20, where $P(n, t)$ is the active power

demand for node n at time t . In this case, each value of $s_{n,t}$ will be defined by the process of MAP.

$$SE(t) = \sum_{n \in N} P(n, t) \cdot s_{n,t}, \forall t \in \{0, \dots, T_h\} \quad (20)$$

To consider the influence of the disruptive event on the probabilities of the DBN and into the final resilience curve, the 5-bus IEEE test case, shown in Fig. 13a, is used for the simulations presented hereafter. The reliability functions for the CPTs are fixed in $f(t) = 0.1$ and $r(t) = 0.1$, as typical values from the literature [22]. Finally, 3 distinct disruptive event scenarios are considered, as presented in Table 1. Scenario 1 and 2 show the same element being in failure (Load 3), but with a higher time to repair for Scenario 2. Additionally, Scenario 3 has the same time to repair as Scenario 2, but with more elements being in failure (both Feeder and Load 3). With this, it is possible to verify the influence of the time to repair itself (duration of the failure) and the number of components being in failure (intensity of the disruptive event).

Table 1 3 possible scenarios representing disruptive events, which are simulated in the 5-bus IEEE test case, shown in Fig. 13a

Scenario number	Node to failure	Time to failure (h)	Time to repair (h)
Scenario 1	Load 3	4	3
Scenario 2	Load 3	4	6
Scenario 3	Feeder and load 3	4	6

For each scenario, the set of nodes to fail, the failure instant and the repair time are defined

Figure 14 illustrates the evolution of Supplied Energy for the 5-bus test case across the different simulated scenarios. Given that the time to failure is equal for all nodes (occurring at $t = 4$ hours), the decline in Supplied

Energy is synchronized. In Scenarios 1 and 2, only a portion of the energy supply is disrupted since a single node goes to a failure state. Conversely, in Scenario 3, where the entire feeder is compromised, the energy supply to all nodes ceases, resulting in a system collapse, i.e., $SE(t = 4 \text{ hours}) = 0$. This showcases the method's capability to model disruptive events of varying severity.

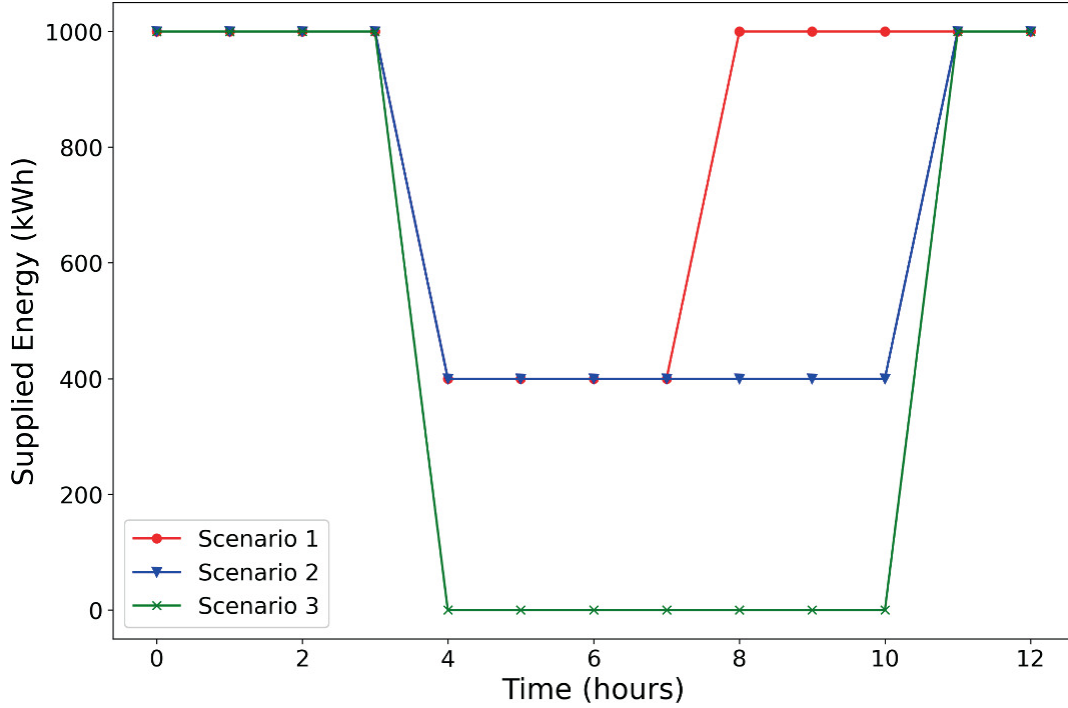


Fig. 14 Evolution of the Supplied Energy of the 5-bus IEEE test case, shown in Fig. 13. Each scenario presented in Table 1 is simulated, by applying evidence propagation coupled with MAP, to define the most probable resilience curve in each case

Furthermore, in Fig. 14, when comparing Scenarios 1 and 2, we observe that despite both scenarios experiencing the same initial performance decline (attributed to the failure of Load 3), Scenario 2 has a longer period of partial energy supply due to the modeled disruptive event having a 6-hour repair time. In contrast, Scenario 1 features a shorter 3-hour repair time, allowing it to return to normal conditions more swiftly. This demonstrates the DBN's

capacity to represent disruptive events with differing durations.

Lastly, it is important to emphasize the DBN's capability to model not only the most probable scenarios (utilizing the concept of MAP) but also to dynamically recalculate the probabilities of a specific component experiencing failure at various time intervals, taking into account the simulated disruptive event. The updated Conditional Probability Tables (CPTs) of the DBN, computed through evidence propagation, serve to verify these probabilities, as illustrated in Table 2.

The DBN can reevaluate the probability that a node will be in a failure state at future time points (e.g., $t = 6$, $t = 9$, and $t = 12$) compared to initial evidence from previous times. All failures commence at $t = 4$, as depicted in Table 1. Notably, it becomes evident that the probability of Load 4 being in a failure state increases with the severity of the scenarios: from Scenario 1 to Scenario 2, where the time to repair is extended, and from Scenario 2 to Scenario 3, where the number of components in failure is greater. This is anticipated since both the feeder and Load 3 are components along the electrical path to Load 4 (as shown in Fig. 11). This feature facilitates sensitivity analysis of the system's failure response, allowing for an assessment not only of the overall probability trend (whether it increases or not) but also its magnitude (i.e., the numerical change in the final probability).

Table 2 Failure probability of Load 4 over different time intervals, with varying simulated Scenarios (Table 1 presents each scenario separately), illustrates the impact of evidence propagation on updating probabilities in each scenario

Scenario number	Probability that Load 4 is in failure at $t = 6$ h	Probability that Load 4 is in failure at $t = 9$ h	Probability that Load 4 is in failure at $t = 12$ h
Scenario 1	0.724	0.729	0.699

Scenario number	Probability that Load 4 is in failure at t = 6 h	Probability that Load 4 is in failure at t = 9 h	Probability that Load 4 is in failure at t = 12 h
Scenario 2	0.744	0.756	0.737
Scenario 3	1.000	1.000	0.878

4 Case Study

In order to allow a better comprehension of the impact of the proposed Multilayer Resilience Assessment, which integrates the models and algorithms presented in Sect. 3, it will be applied to a test case in which a power distribution system was built upon a real road network, a summary of the test case data is presented in Table 3. The system's electrical and geographical features are available in [54], and more details about it can be found in [49].

Table 3 Summary of the test case used in this case study, the data is available in [54]

Feature	Quantity
Substations	2
Feeders	4
Load nodes	68
Switches	46
Sectors	37
Customers	4697
Road network nodes	928
Road network edges	2309

The initial step of the simulation involves assessing the failure probabilities of all sectors within the test case by utilizing the DBN, where each sector is represented as a distinct node. To this end, the baseline curves presented in Figs. 5 and 6 were used for the repair duration (or failure duration) and time to failure occurrence models,

respectively. These models provide the failure and repair probabilities, $f(t)$ and $r(t)$, which are processed by the DBN and generate a conditional failure probability for each sector. Figure 15 illustrates such failure probabilities across the entire system. Notably, the DBN's capability to consider the system's granularity enables the calculation of distinct failure probabilities for each sector. This granularity proves instrumental in informing the restoration algorithm, allowing sectors with higher failure probabilities to be prioritized during restoration efforts. Such prioritization ensures a strategic approach to system restoration, enhancing overall efficiency and resilience.

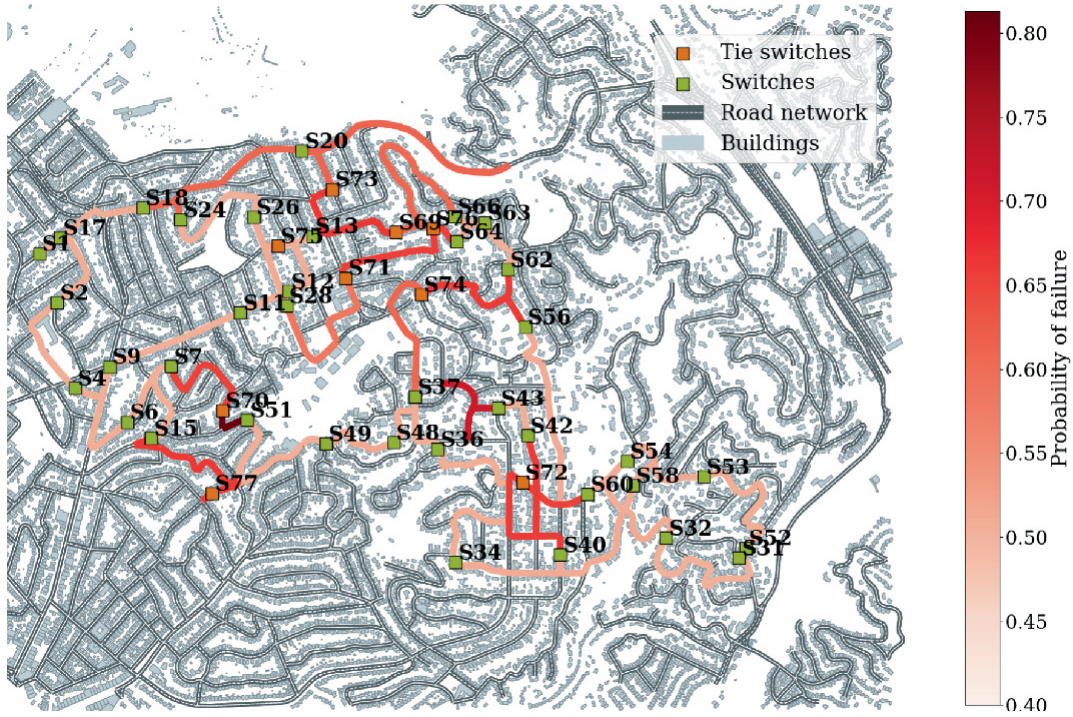


Fig. 15 Spatial distribution of the probabilities of failure engendered by the DBN builder using the failure duration and time to failure models

The variability in the probabilities of failure, as illustrated in Fig. 15, is closely tied to the structural arrangement of the DBN. The nodes' probability of failure is determined by the failure duration and time to occurrence models fitted to historical data. However, nodes with multiple paths to the feeder have a lower chance of

power interruption, as the loss of power along the energized path can be restored by alternative paths. Importantly, these probabilities represent prior probabilities, capturing the likelihood of failure when no other sections are compromised. These initial probabilities of failure provide a baseline for simulating individual points of failure within the system and guiding the restoration process effectively.

Figure 16 illustrates a fault case with six out-of-service sectors affecting 987 customers, which is more than 20% of the total customers served by the distribution system. There are several ways to patrol and restore power to the out-of-service customers. One possible solution would be to patrol and restore power to one sector at a time. For example, opening device S18 and closing S17 would restore power to the first sector after patrolling it. Then, the sector between switches S20, S18, and S24 could be patrolled and restored, and this process goes on until a fault is found and repaired or all the sectors are restored. However, managing so many switches can not be the better solution due to dislocation and patrolling times summed with the operation time of all the switches, which involves isolating traffic with signalization and preparing their security apparatus before climbing the pole to operate each device.

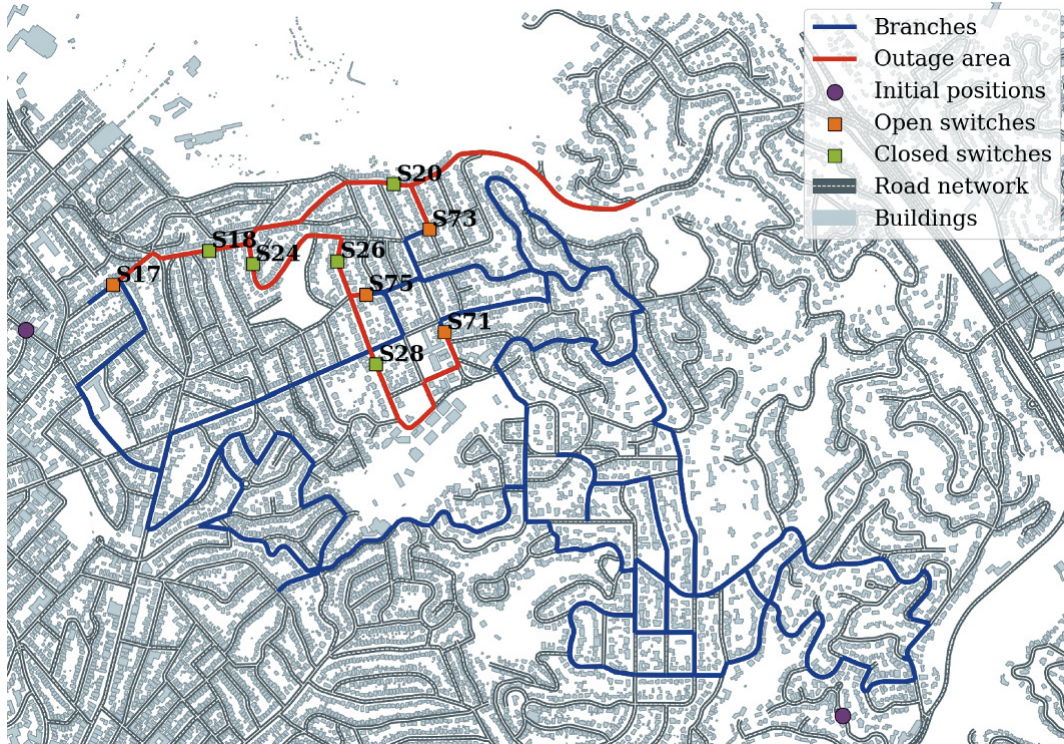
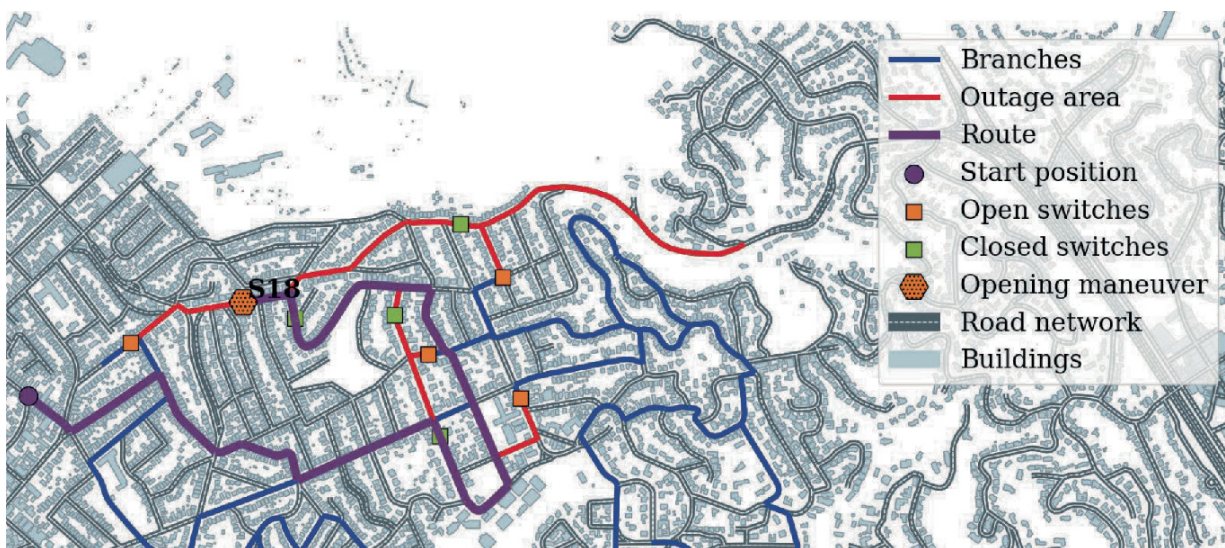


Fig. 16 Illustrated as a spatial depiction of the outage area consisting of six sectors, the initial positions of the two available crews were randomly selected from the road network using a uniform distribution. Initially, the outage area is isolated due to an event-triggering device S17. Furthermore, devices S71, S73, and S75 are tie switches capable of transferring the outage area to another feeder and restoring all the unserved customers. This situation includes a count of 987 disconnected customers

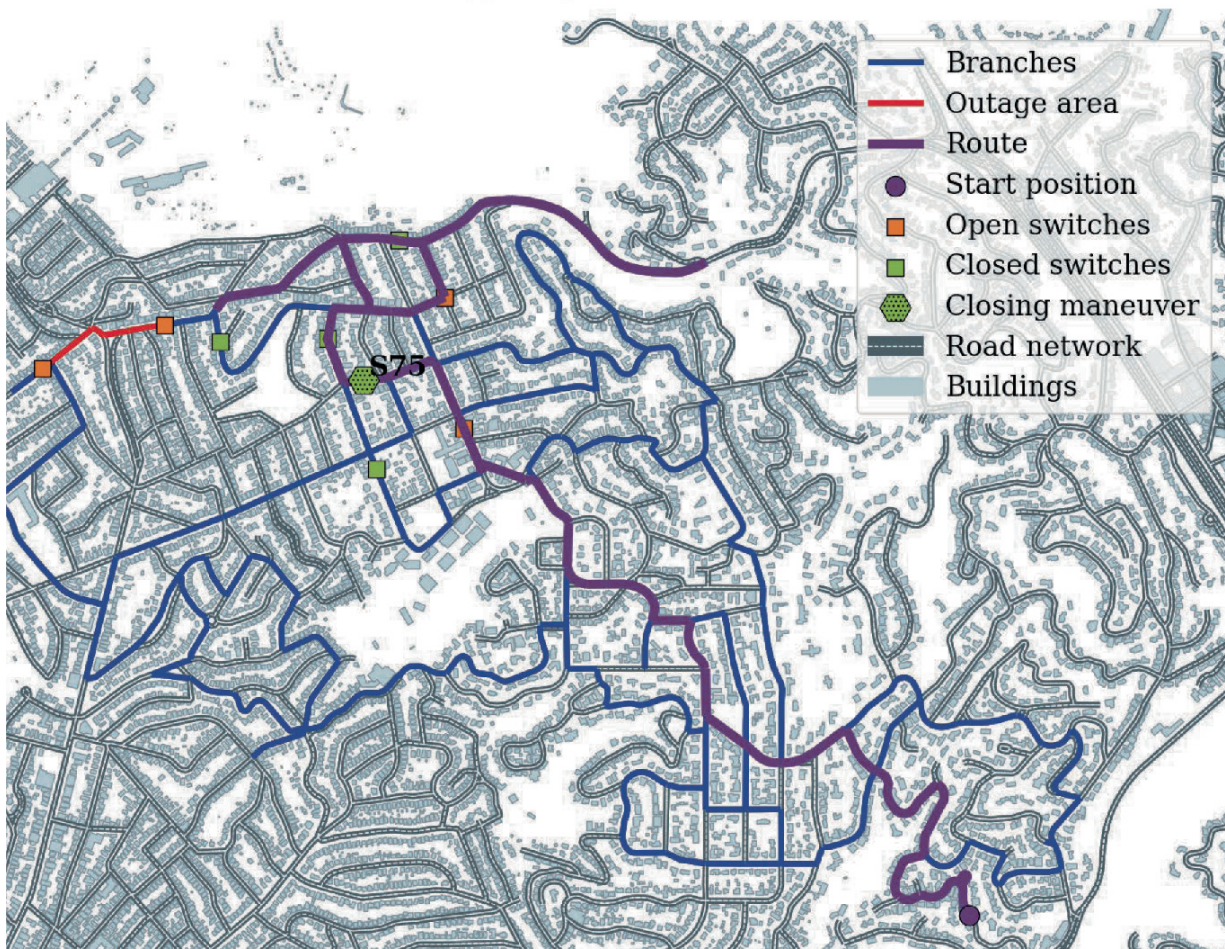
Another solution would be to patrol the entire outage area and close switch S17 after clearing any fault. This patrolling strategy is widely used by utilities but can also be time-consuming, especially in rural areas. An optimized strategy would combine the best of both worlds: patrolling several sectors at once and operating fewer devices. The service restoration described in Sect. 3.3 provides such optimization from the patrolling perspective by uniting nearby sectors into a single restoration stage. The multilayer approach enables a resilience assessment considering such efficient solutions and is illustrated in the conditions outlined in Fig. 16.

The optimized restoration process, which is considered during the resilience estimation, is executed in two stages.

Figure 17 illustrates the first stage of the service restoration with two crews. In the first phase, crew 1 patrols the lower sections of the network, relocates to device S18, and opens it, effectively isolating this sector from the broader network. Meanwhile, the second crew inspected the remaining nodes within this network and closed the tie switch S75, restoring power to 934 customers in 26.4 minutes. The second stage is presented in Fig. 18. In the final stage of power restoration, crew 1 is assigned the task of maneuvering the sectionalizing device S18 to restore power to the remaining sector, which has the last 53 de-energized customers.



(a) Stage 1 - Crew 1.



(b) Stage 1 - Crew 2.

Fig. 17 First stage of the optimized restoration process for the case in Fig. 16. Crew 1 patrols a portion of the network before advancing to S18 and opening it, separating this sector from the rest of the network. After inspecting the complementary nodes in the outage area, crew 2 closes S75 to restore power to most de-energized customers



Fig. 18 Second stage of the optimized restoration process for the case in Fig. 16. After the switch maneuvers at stage 1, crew 1 patrols the remaining outage area in the second stage and reenergizes it by shutting device S18. In this last step, crew 2 remains idle and therefore is released for another occurrence

This example incorporates the complete approach for patrolling optimization, i.e., the bi-level optimization algorithm from Sect. 3.3 and the probabilities of failure generated by the DBN by using the failure duration and time to failure models from Sect. 3.2 and shown in Fig. 15. In the outage area, a sector experiences the least service interruptions. As depicted in Fig. 15, this sector is between switches S17 and S18. As a result, it is given lower priority during patrol and restoration. In the final stage of restoration, this sector is shown being restored in Fig. 18. This is an intriguing result if compared to the approach commonly used by utilities, which involves scanning the outage area in the downstream direction by following the topological sort. Such an empirical approach employed by the utilities would start the service restoration in this sector, making the network less resilient.

Besides integrating the optimal service restoration process during resilience assessment, another crucial aspect of the proposed multilayer approach is its capability to assess the system's resilience across various weather conditions. This evaluation relies on the Reliability Curves depicted in Figs. 5 and 6, which illustrate failure duration and time to failure occurrence, respectively. Three distinct weather scenarios are examined: 'Wind Speed = 10 km/h, AtDisc = 0' (mild weather); 'Wind Speed = 45 km/h, AtDisc = 100' (moderate severity weather); and 'Wind Speed = 90 km/h, AtDisc = 1000' (extreme severity weather). A unique DBN is constructed for each weather condition, incorporating differing failure duration and lifetime distributions. Specifically, the failure duration model informs the assessment of the interruption of a failure for each power system sector, while the lifetime is utilized to determine the failure probability. The probability of failure, in turn, serves as a weighting factor in the routing algorithm, prioritizing nodes with the highest probabilities for visitation. Moreover, the duration is utilized to calculate the duration of the repair crew's stay at each node before proceeding to the next.

Following the application of the service restoration algorithm, it becomes feasible to analyze the sectors that remained disconnected and for what duration. Figure 19 illustrates the progression of the supplied energy over time, incorporating the two-step restoration process outlined in this section and considering the effects of the weather scenarios described in the previous paragraph. Initially, at the onset of the simulation, all nodes are operational, resulting in 100% supplied energy. The restoration process comprises two distinct steps, with the duration of each step influenced by weather variables. Harsher weather conditions lead to longer average failure duration, as depicted in the resilience curve. Consequently, during severe weather events, the system takes more time to

return to its normal operational state (supplied energy of 1). For instance, a scenario of low severity (blue curve) requires approximately 100 mins for full restoration, while extreme severity conditions (green curve) entail nearly 1000 mins.

In reference to Fig. 19, it is essential to consider that, although the total duration for complete system restoration (achieved when supplied energy reaches 1) varied across different weather conditions, the initial drop in supplied energy (approximately to 0.86) and the state of partial repair (with supplied energy at 0.94) remained consistent across all three weather scenarios. This consistency may appear unusual; however, it stems from the simulation procedure, wherein the sector with the highest failure rate-mode of the spatial distribution-was deliberately chosen to experience a failure state. Despite variations in weather conditions affecting the probability of failure, they do not alter the identity of the sector with the highest failure probability relative to others. Consequently, irrespective of the weather conditions, the same sector experiences failure. Hence, while the timing of repair steps differs depending on the weather conditions, they yield the same performance drop value due to the uniformity in the sector experiencing failure across all evaluated scenarios. As a result, the maintenance teams isolated the affected sector and brought power back to the others before re-energizing the sector between the switches S28 and S71, which was the source of the incident. In this case, the switching operations produced discontinuities in the supplied energy curves.

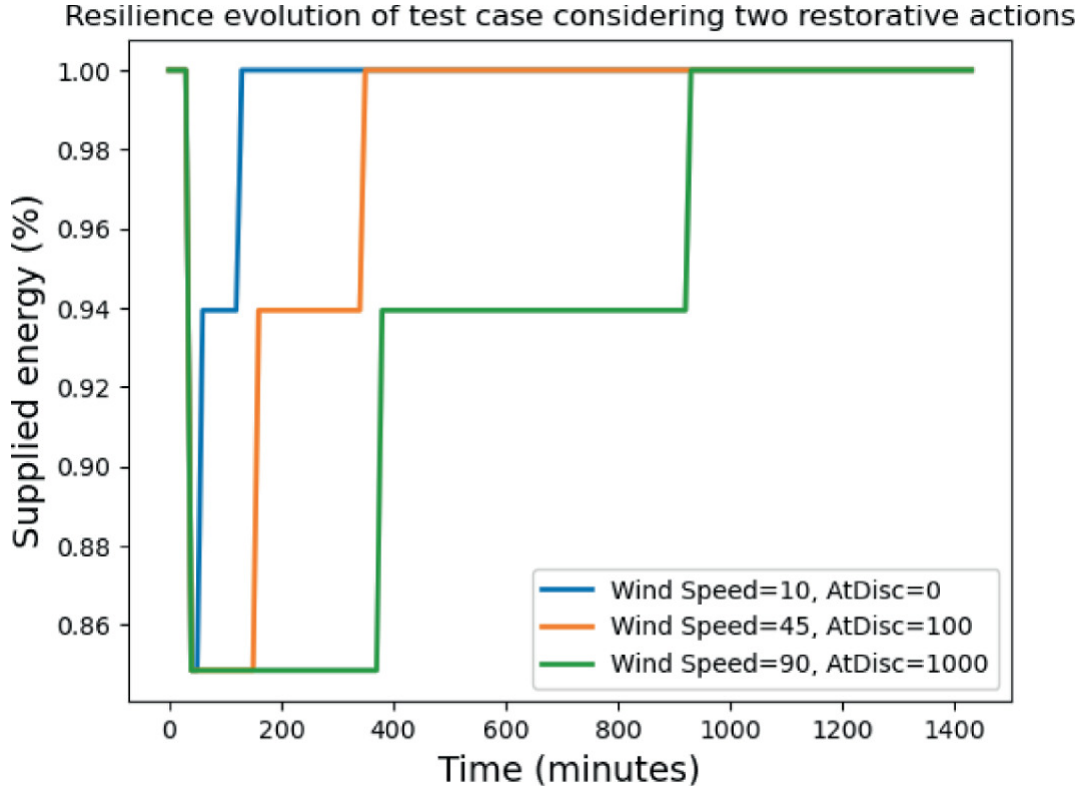


Fig. 19 Resilience over time for the restoration process conducted in the case study. The performance function shown is supplied energy

Such findings underscore the proposed approach's capability not only to statistically model weather variables within reliability curves but also to translate these curves into resilience assessment within a power system, accounting for the service restoration process. Such capability produces specific results that are different from the ones illustrated in Sect. 3.4, where only repair was considered. The main differences are related to the weather effect combined with the service restoration in the performance estimation by evidence propagation and MAP inference. From the results in Fig. 19, it is obvious that the system resilience is lower as the weather severity increases, and the effect of service restoration is clear due to the partial performance bounce back.

It is worth noting that the supplied energy levels depicted in Fig. 19 are modeled using the DBN, where the evidence propagation process determines the operational

status of each node at every time interval. To achieve this, a 10-minute time interval was employed for modeling the DBN, providing a finer granularity of the repair process, which typically spans around 60 minutes. The flexibility in choosing the length of the time interval, a parameter set by the user, enables the evaluation of resilience even in scenarios involving swift restorations, such as the one depicted, occurring within an hour. Moreover, this approach accommodates operations that may extend over hours or even days, ensuring comprehensive resilience assessment across varying timescales and conditions.

5 Conclusion

This chapter presented a multilayer approach to assessing the resilience of power distribution systems by integrating different data sources, models, and algorithms. The presented approach integrates reliability regression models to failure occurrence instant and failure duration that take into account for weather variables' effects, a service restoration algorithm to obtain an optimal restoration strategy, and field crew routing, which minimizes the time to service restoration through manual switches operation, and a DBN resilience assessment that uses the reliability regression models and the service restoration algorithm to estimate resilience accounting for all the modeled factors. The integration of these models and algorithms in the multilayer approach is illustrated by a case study with detailed information on the optimized service restoration and the effects on the estimated resilience obtained from the DBN.

Reliability engineering regression is used to evaluate two main measures in the context of power systems: the time between failures and the failure duration. Then, the probabilities related to these two times were used as inputs to the DBN method, where the interactions between

different components in the power system are modeled through the conditional probabilities evaluated by the DBN. Unlike traditional approaches, the proposed technique employs DBNs to model the intricate interactions among diverse components within the power system. By utilizing conditional probabilities computed by the DBN, we gain a comprehensive understanding of how different elements influence each other's behavior and contribute to the overall system response to failures. In addition, a service restoration algorithm was used to allow the use of redundant electrical paths, related to the operation of normally open switches, which is mandatory for a better response to failure occurrences.

Moreover, the versatility of DBNs extends beyond mere modeling; they serve as a powerful tool for resilience assessment. Through MAP inference, combined with evidence propagation techniques, the DBN enables us to evaluate the system's resilience under various scenarios. This dynamic approach allows us to simulate and analyze the system's response to different stressors, such as component failures or external disturbances. By propagating evidence of failures through the network, we can quantify the impact on system performance and identify critical points of vulnerability.

The illustration of the methods separately and the case study with their integration allowed us to show how they affect the resilience estimation, the weather severity is mandatory in the rapidity to recovery all the system performance, and the service restoration is fundamental to exploring the redundancies due to the presence of normally open switches present in power distribution systems. The consideration of all these aspects is fundamental to accurately obtaining a performance estimation, and consequently, the associated system resilience estimation.

This chapter does not explore all the integration possibilities between the presented models and algorithms.

Moreover, other aspects can be relevant to a specific power distribution system, such as other weather variables, and specificities related to the service restoration, for example remotely controlled switches and distributed generation, or even to another critical infrastructure that will demand specific adaptations of the multilayer resilience assessment approach presented here. Furthermore, the presented method can be extended to consider the interdependencies between different systems during resilience assessment, and the resilience estimation can be performed by simulating various trials of the DBN by Monte Carlo approaches instead of using the MAP inference.

Acknowledgements

The authors of this work would like to thank the Center for Artificial Intelligence (C4AI-USP) and the support from the IBM Corporation, São Paulo Research Foundation (FAPESP), grants 2019/07665-4, 2014/50851-0, 2021/12220-1, and 2023/07634-7, BPE Fapesp grant 2018/19150-6, Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), grant 465755/2014-3, Fundação de Amparo à Pesquisa de Minas Gerais (FAPEMIG), and the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES)—Finance Code 001.

References

1. Liu W, Song Z (2020) Review of studies on the resilience of urban critical infrastructure networks. *Reliab Eng Syst Saf* 193:106617 [[Crossref](#)]
2. Bessani M, Fanucchi RZ, Delbem ACC, Maciel CD (2016) Impact of operators' performance in the reliability of cyber-physical power distribution systems. *IET Gen Transm Distrib* 10(11):2640–2646 [[Crossref](#)]

3. Mourtzis D, Angelopoulos J, Panopoulos N (2022) A literature review of the challenges and opportunities of the transition from industry 4.0 to society 5.0. *Energies* 15(17):6276
[\[Crossref\]](#)
4. IPCC (2023) Climate change 2023: synthesis report. a report of the intergovernmental panel on climate change. In: Contribution of working groups i, ii and iii to the sixth assessment report of the intergovernmental panel on climate change. Tech. rep., [Lee H, Romero J (eds) Core writing team]. Geneva, Switzerland
5. Cybersecurity and I. S. Agency (2019) A guide to critical infrastructure security and resilience
6. National Academy of Sciences (NAS) (2012) Disaster resilience: a national imperative. The National Academies Press, Washington, D.C.
7. Poulin C, Kane MB (2021) Infrastructure resilience curves: performance measures and summary metrics. *Reliab Eng Syst Saf* 216:107926 Dec.
[\[Crossref\]](#)
8. Iannacone L, Sharma N, Tabandeh A, Gardoni P (2022) Modeling time-varying reliability and resilience of deteriorating infrastructure. *Reliab Eng Syst Saf* 217:108074 Jan.
[\[Crossref\]](#)
9. Suo W, Wang L, Li J (2021) Probabilistic risk assessment for interdependent critical infrastructures: a scenario-driven dynamic stochastic model. *Reliab Eng Syst Saf* 214:107730
[\[Crossref\]](#)
10. Wang Y, Zio E, Wei X, Zhang D, Wu B (2019) A resilience perspective on water transport systems: the case of eastern star. *Int J Dis Risk Red* 33:343–354
11. Bešinović N (2020) Resilience in railway transport systems: a literature review and research agenda. *Transp Rev* 40(4):457–478
[\[Crossref\]](#)
12. Righi AW, Saurin TA, Wachs P (2015) A systematic literature review of resilience engineering: research areas and a research agenda proposal. *Reliab Eng Syst Saf* 141:142–152
[\[Crossref\]](#)
13. Brown RE (2017) Electric power distribution reliability, vol 1. CRC press
14. Geng S, Yang M, Mitici M, Liu S (2023) A resilience assessment framework for complex engineered systems using graphical evaluation and review technique (GERT). *Reliab Eng Syst Saf* 236:109298 Aug.

- [\[Crossref\]](#)
15. Wu J, Yu Y, Yu J, Chang X, Xu L, Zhang W (2023) A Markov resilience assessment framework for tension leg platform under mooring failure. *Reliab Eng Syst Saf* 231:108939 Mar. [\[Crossref\]](#)
 16. Cheng Y, Elsayed E, Chen X (2021) Random multi hazard resilience modeling of engineered systems and critical infrastructure. *Reliab Eng Syst Saf* 209:107453 May [\[Crossref\]](#)
 17. Bessani M, Massignan JA, Fanucchi RZ, Camillo MH, London JB, Delbem AC, Maciel CD (2018) Probabilistic assessment of power distribution systems resilience under extreme weather. *IEEE Syst J* 13(2):1747–1756 [\[Crossref\]](#)
 18. Caetano HO, Desuó L, Fogliatto MS, Maciel CD (2023) Distribution systems cost reduction based on switches upgrades: a stochastic approach. *Electr Power Syst Res* 216:108523 [\[Crossref\]](#)
 19. Ma X, Zhou H, Li Z (2021) On the resilience of modern power systems: a complex network perspective. *Renew Sustain Energy Rev* 152:111646 [\[Crossref\]](#)
 20. Haque MA (2018) Analysis of bulk power system resilience using vulnerability graph. Old Dominion University
 21. Force IPT, Stanković A, Tomsovic K, De Caro F, Braun M, Chow J, Āukalevski N, Dobson I, Eto J, Fink B et al (2022) Methods for analysis and quantification of power system resilience. *IEEE Trans Power Syst*
 22. Caetano HO, Desuó L, Fogliatto MS, Maciel CD (2024) Resilience assessment of critical infrastructures using dynamic Bayesian networks and evidence propagation. *Reliab Eng Syst Saf* 241:109691 [\[Crossref\]](#)
 23. Pearl J (2011) Bayesian networks
 24. Robinson JW, Hartemink AJ (2010) Learning non-stationary dynamic Bayesian networks. *J Mach Learn Res* 11(118):3647–3680 [\[MathSciNet\]](#)
 25. Zlotecka D, Sroka K (2018) The characteristics and main causes of power system failures basing on the analysis of previous blackouts in the world. In: 2018 International interdisciplinary Ph.D. workshop (IIPhDW). IEEE
 26. Wang F, Li L, Li C, Wu Q, Cao Y, Zhou B, Fang B (2018) Fractal characteristics analysis of blackouts in interconnected power grid. IEEE

Trans Power Syst 33:1085–1086 Jan.

[\[Crossref\]](#)

27. Veloza OP, Santamaria F (2016) Analysis of major blackouts from 2003 to 2015: classification of incidents and review of main causes. *Electricity J* 29:42–49 Sept.
[\[Crossref\]](#)
28. De La Ree J, Liu Y, Mili L, Phadke A, DaSilva L (2005) Catastrophic failures in power systems: causes, analyses, and countermeasures. *Proc IEEE* 93:956–964 May
[\[Crossref\]](#)
29. Fan Y, Mengnuo D, Pei G, Zhang Z, Yingying L, Xiao W (2018) The influence on distribution network planning and investment strategy of power grid corp under electric power system reform. In: 2018 China international conference on electricity distribution (CICED). IEEE
30. Costa MM, Bessani M, Batista LS (2021) A multiobjective and multicriteria approach for optimal placement of protective devices and switches in distribution networks. *IEEE Trans Power Deliv* 37(4):2978–2985
[\[Crossref\]](#)
31. Wu J, Wu Z, Wu F, Mao X (2017) A power balancing method of distributed generation and electric vehicle charging for minimizing operation cost of distribution systems with uncertainties. *Energy Sci Eng* 5:167–179 June
[\[Crossref\]](#)
32. Ahadi A, Ghadimi N, Mirabbasi D (2014) An analytical methodology for assessment of smart monitoring impact on future electric power distribution system reliability. *Complexity* 21:99–113 May
[\[Crossref\]](#)
33. Xu SY, Chen MY, Wade N, Li R (2011) Reliability evaluation of electric power system containing distribution generation. *Adv Mater Res* 383–390:3472–3478 Nov.
[\[Crossref\]](#)
34. Karpov AI, Akimov DA (2018) Integral indicators improvement (saifi) of power supply reliability in electric distribution systems based on reclosers placement optimization. In: 2018 IEEE conference of Russian young researchers in electrical and electronic engineering (EIConRus). IEEE
35. Rod B, Barabadi A, Naseri M (2020) Recoverability modeling of power distribution systems using accelerated life models: case of power cut due to extreme weather events in Norway. *J Manage Eng* 36(5):05020012
[\[Crossref\]](#)

36. Chen C, Chen B (2018) Modernizing distribution system restoration to achieve resiliency against extreme weather events. In : 2018 IEEE global conference on signal and information processing (GlobalSIP). IEEE
37. Figueroa-Candia M, Felder FA, Coit DW (2018) Resiliency-based optimization of restoration policies for electric power distribution systems. *Electric Power Syst Res* 161:188–198 Aug.
[\[Crossref\]](#)
38. Chen C, Wang J, Ton D (2017) Modernizing distribution system restoration to achieve grid resiliency against extreme weather events: an integrated solution. *Proc IEEE* 105:1267–1288 July
[\[Crossref\]](#)
39. Fanucchi RZ, Bessani M, Camillo MHM, London JBA, Maciel CD (2016) Failure rate prediction under adverse weather conditions in an electric distribution system using negative binomial regression. In: 2016 17th International conference on harmonics and quality of Power (ICHQP). IEEE, pp 478–483
40. Su P, Lin CK, Hung J, Lee J (2022) The proper use and reporting of survival analysis and cox regression. *World Neurosurg* 161:303–309
[\[Crossref\]](#)
41. Bessani M, Fanucchi RZ, Achcar JA, Maciel CD (2016) A statistical analysis and modeling of repair data from a brazilian power distribution system. In: 2016 17th International conference on harmonics and quality of power (ICHQP), pp 473–477
42. Fogliatto MS, Ribeiro RR, Monteiro JR, London J, Bessani M, CMaciel CD et al (2022) Lifetime study of electrical power distribution systems failures. *J Control Autom Electric Syst*, pp 1–11
43. Fogliatto MS, Caetano HO, Massignan JA, Fanucchi RZ, London JB Jr, Pereira BR Jr, Bessani M, Maciel CD (2022) Power distribution system interruption duration model using reliability analysis regression. *Electric Power Syst Res* 211:108193
[\[Crossref\]](#)
44. Chen B, Ye Z, Chen C, Wang J, Ding T, Bie Z (2019) Toward a synthetic model for distribution system restoration and crew dispatch. *IEEE Trans Power Syst* 34(3):2228–2239
[\[Crossref\]](#)
45. Zhang G, Zhang F, Zhang X, Meng K, Dong ZY (2020) Sequential disaster recovery model for distribution systems with co-optimization of maintenance and restoration crew dispatch. *IEEE Trans Smart Grid* 11(6):4700–4713

- [\[Crossref\]](#)
46. Bahmanyar A, Jamali S, Estebsari A, Bompard E (2017) A comparison framework for distribution system outage and fault location methods. *Electric Power Syst Res* 145:19–34
[\[Crossref\]](#)
 47. Nagy AM, Simon V (2018) Survey on traffic prediction in smart cities. *Perv Mob Comput* 50:148–163
[\[Crossref\]](#)
 48. Liu J, Wu N, Qiao Y, Li Z (2021) A scientometric review of research on traffic forecasting in transportation. *IET Intell Transp Syst* 15(1):1–16
[\[Crossref\]](#)
 49. Desuó NL, Fogliatto MSS, Caetano HO, Pereira BR, London JBA, Maciel CD (2024) A multilayer system and optimization framework for team dispatch towards service recovery. *IEEE Trans Reliab* 73(1):156–169
[\[Crossref\]](#)
 50. AlMuhaini M, Ilius P, AlOwaifeer M (2022) Intelligent load prioritization sequence for distribution system reconfiguration. In: 2022 IEEE/PES transmission and distribution conference and exposition (T &D), pp 1–5
 51. Marques LT, Delbem ACB, London JBA (2018) Service restoration with prioritization of customers and switches and determination of switching sequence. *IEEE Trans Smart Grid* 9(3):2359–2370
 52. Thekumparampil KK, Jain P, Netrapalli P, Oh S (2019) Efficient algorithms for smooth minimax optimization. In: Wallach H, Larochelle H, Beygelzimer A, d'Alché-Buc F, Fox E, Garnett R (eds) *Advances in neural information processing systems*, vol 32. Curran Associates, Inc., pp 12680–12691
 53. Wirsansky E (2020) *Hands-on genetic algorithms with python: applying genetic algorithms to solve real-world deep learning and artificial intelligence problems*. Packt Publishing
 54. Dezueto Neto L, London Jr JBA, Maciel CD, Pereira Jr BR (2021) Dataset for patrol sequences of out-of-service nodes in a power distribution feeders

Economic and Resilience Improvement for Radial and Meshed Grids

Enrique Rosales-Asensio^{1, 2} , Miguel de Simón-Martín^{1, 2}, Jorge Blanes-Peiró^{1, 2}, Alberto González-Martínez^{1, 2} and Antonio Colmenar-Santos^{2, 3}

- (1) University of Las Palmas de Gran Canaria, Campus de Tafira s/n, 35017 Las Palmas de Gran Canaria, Canary Islands, Spain
- (2) Departamento de Ingeniería Eléctrica y de Sistemas y Automática, Escuela de Ingenierías Industrial E Informática Campus de Vegazana, Universidad de León, s/n, 24071 León, Spain
- (3) Department of Electrical Engineering, Electronics, Control, Telematics and Chemistry Applied to Engineering, UNED, Juan del Rosal, 12, Ciudad Universitaria, 28040 Madrid, Spain

 **Enrique Rosales-Asensio**
Email: enrique.rosales@ulpgc.es

Abstract

A resilient photovoltaic system, which comprises the joint use of photovoltaic solar panels and electrochemical storage that is capable of operating both with and without grid connection, is capable of providing an added service both during normal grid-connected operation and when a blackout occurs (as opposed to a traditional solar system, which is only operational when the grid is operational). When the conventional power grid is in normal operation, resilient photovoltaic systems are able to generate revenue and/or reduce the electricity bill. During blackouts, resilient photovoltaic systems are capable of providing critical emergency power. The research presented here evaluates the technical and economic feasibility of systems based on photovoltaic solar energy and electrochemical storage in three critical infrastructures. To this end, the research presented here assigns a monetary value to the cost of avoiding a blackout. The research presented here used REOpt software to optimally select and dimension different resilient schemes. For each of the cases evaluated the resilient systems were able to obtain benefits associated with the substitution of the energy use of the electricity grid, the reduction of charges for the use of energy during peak energy periods, and the modification of energy purchase periods from periods of high cost to periods of low cost. For all cases the model found the optimal combination of technologies capable of minimizing the cost of energy throughout the life cycle of the project. The results of the research presented showed that assigning a value to the cost of blackouts can have a major impact on the economic viability of a resilient solution. For all cases the

net present value of a system was always higher when a value was assigned to resilience. The values assigned to resilience were higher for users of radio networks, which are more prone to blackouts, and lower for users with meshed networks, which enjoy more reliable networks. Despite the fact that for the investigation presented here only three types of infrastructure were assessed, similar results could be expected for other critical infrastructure with similar loads and electricity tariffs. Resilient systems using photovoltaic solar panels that are limited in size could provide both economic savings during normal grid-connected operation and limited emergency power during blackouts. When these systems based on photovoltaic solar energy and electrochemical storage are used in conjunction with an emergency diesel group, these resilient “hybrid” systems are capable of satisfying critical loads during short and long term blackouts.

Keywords Solar-plus-storage – Radial grid segments – Network grid segments – Economic analysis – Resiliency analysis

Nomenclature

ASHRAE American society of heating, refrigerating and air-conditioning engineers

CAIDI Customer average interruption duration index

FDNY Fire Department of the City of New York

GW Gigawatt

ICE Interruption cost estimator

MEP Mechanical, electrical and plumbing

NYPD New York City police department

PV Photovoltaics

SAIFI System average interruption frequency index

U.S. The United States of America

1 Introduction

The resilience of electrical systems focuses on preventing power outages, protecting life and goods dependent on the electricity service [1] as well as minimising the time needed to restore service and recovering the electricity supply [2]. As climate change leads to increasingly severe and frequent devastations around the world, strengthening the resilience of energy infrastructure has become an urgent priority [3, 4], particularly in shelters, hospitals and emergency supply stores [5]. Although standby power sources usually run on gas and diesel generators [6], the use of microgrids also has potential applications in terms of energy resilience and safety [7].

Total losses resulting from natural disasters in the United States have exceeded \$50 billion per year in five of the 10 years from 2003 to 2013 [8]—note the fact that, on average, those countries with longer durations of power outages experience higher sales losses [9]. In some cases, the lack of backup

power has meant that it has been impossible to feed critical loads for several days [10]. As far as fuel supply is concerned, it should be borne in mind that, although pipelines are highly resistant to inclement weather, they have the drawback of potentially being able to break or be damaged—this would have to be closely monitored to prevent any small problem from becoming a major problem if there is an interruption in fuel supply [11]. Finally, it should also be noted that weather phenomena combined with outdated infrastructure could increase the risk of blackouts [12].

Exemplifying what was said in previous paragraphs through the problem associated with Hurricane Sandy, it should be noted that after large portions of New York City suffered a power outage at approximately 8:00 PM on Monday, October 29, 2012, the city deployed as many generators as it could to satisfy a demand that exceeded the number of requests for any other incident [13]. In total, the city deployed approximately 230 generators in hospitals, nursing homes and large multi-family buildings [13]. As far as New York City is concerned, the amount of hazardous materials stored and used temporarily cannot exceed 5 gal of gasoline, or 250 gal of any other flammable liquid, and 300 gal of any combustible liquid—the storage or use of hazardous materials in quantities greater than these quantities requires a specific permit for each place where such storage or use occurs [14]. Assuming a building equipped with a 175 kW diesel generator, a 250 gal (946 L) fuel tank and a consumption of 10.5 gal/h (40 L/h) [15], the fuel would run out in less than 24 h. As part of the 2011 reliability report, the Consolidated Edison Company of New York identified a total of six major storms affecting radio customers and four winter snow/ice events affecting mesh customers¹ [17].

Including major storms, the average duration per affected customer (CAIDI) for radio networks in New York between 2012 and 2016 was 35.28 h on average per year; while the average duration per affected customer (CAIDI) for networks in New York during that period was 7.9 h on average per year. That said, in 2012 the average duration per affected customer was 102.05 and 6.33 h respectively [18]. Overall, for 3 days after Sandy, all fuel terminals in the New York metropolitan region were completely out of service [19]. Even 10 days after the storm, only 79% were operational [19]. As a result of Hurricane Sandy, New York required substantial amounts of fuel for critical energy restoration and emergency public transportation [20]. In this case, the Federal Emergency Administration, as a result of the consequences of this hurricane, had to pay 6.37 million dollars for 1.7 million gallons of gasoline [20].

These types of disasters cause widespread and long-lasting disruptions and lead to loss of production, wages and inventory [21]. Between 2003 and 2012, climate-related disruptions are estimated to have cost the U.S. economy an annual inflation-adjusted average of \$18 trillion to \$33 trillion. Annual costs fluctuate significantly and are highest in the years of major storms, such as Hurricane Ike in 2008, when cost estimates range from \$40 to \$75 billion, and Hurricane Sandy in 2012, when cost estimates range from \$27 to \$52 billion [22]. In the event of a power outage in end uses such as hospitals and electronic medical equipment ceasing to function, the effect on patients could be fatal

[23]. Although it is impossible to make a precise estimate of the cost of blackouts [24, 25], that cost exists.

Resilient photovoltaic solar energy is characterized by the fact that it is coupled with a technology that allows it to continue providing energy during power outages [26]. Currently, traditional photovoltaic systems are configured to shut down during power outages [26]. This configuration protects the safety of the workers of the electricity distributors [26]. However, if configured to enhance resilience, photovoltaic solar energy can continue to operate and supply power during power outages [26]. There are three standard ways to make PV resilient [26]:

1. Coupling solar modules with batteries to store energy for later use (this is known as photovoltaic solar energy with battery backup).
2. Coupling solar energy with auxiliary generation like a diesel generator.
3. Using an inverter with an emergency power socket that provides limited power

It should be noted that the addition of battery storage to photovoltaic solar panels (i) can improve the viability of projects by reducing the costs associated with electricity demand as well as (ii) serve as an opportunity to align the sustainability and resilience goals of cities [27]. In most solar photovoltaic + storage applications, investors are responsible for (i) making decisions about charging batteries, (ii) providing electricity to the load, and/or (iii) providing electricity to the grid [28]. With the right switches, inverters also allow photovoltaic panels and storage (and/or other distributed generators) to function as an “isolated” microgrid, providing electricity to an individual building or to a separate community and independent of the primary power grid [28].

The current cornerstone of resilience, the generation of fossil fuel reserves, is useful for overcoming short outages, but for longer outages these systems are vulnerable to fuel supply chains that may be, and have been, compromised due to physical damage to transport and distribution infrastructure [21]. Hybrid renewable energy systems can serve as an alternative or complement to existing forms of backup power, extending the limited supply of fuel and providing greater system redundancy [21]. A renewable energy hybrid system can withstand longer interruptions for a given amount of diesel fuel by reducing the operating time (and therefore fuel consumption) of the diesel generator, thereby increasing the site's energy resistance [21]. A hybrid renewable energy system can also expand the scale of available backup energy by extending backup power to loads that would not otherwise be powered [21]. In addition, these hybrid renewable energy systems can be operated for economic gain when the network is in operation, offsetting energy purchases, reducing peak demand charges, performing energy arbitrages and providing ancillary services [21]. In addition, other smaller-scale renewable resources, such as biomass, geothermal and hydropower, can also complement solar energy by providing

rapid-dispatchable back-up energy or base-load energy similar to that provided by fossil and nuclear energy [29].

Between 2011 and 2016, New York increased its use of solar energy by almost 800% [30]. The State Energy Plan is a comprehensive roadmap for building a clean, resilient and affordable energy system for all New Yorkers [31]. The initiatives outlined in the State Energy Plan, along with private sector innovation and the investment driven by “Energy Vision Reform”, will put New York State on track to achieve 50% of electricity from renewable energy sources [31] and expand New York's distributed solar energy target by 2025 to 6 GW [32].

Electricity storage systems allow higher levels of intermittent renewable generation, which can help overcome the barriers associated with new renewable energy projects [33]. Solar energy and storage are strongly synergistic, with combined net present values that are significantly higher than the sum of individual net present values for solar energy and storage alone [34]. Distributed energy resources, such as energy storage and combined solar storage systems, are increasingly valuable both to the New York grid and to the commercial and industrial energy consumers who depend on it [35]. The ability of commercial and industrial energy consumers to generate, store, consume and share low-cost energy can significantly offset energy costs, while making the network cleaner and less costly to operate [35]. With the goal of expanding New York's distributed solar power by 2025 to 6 GW [32], the research presented here aims to conduct an economic and resilience analysis of the benefits of introducing photovoltaic solar power and storage in end-users located in radial and meshed networks.

In the scientific literature, it is possible to find a large number of research papers exploring how to improve the resiliency of electricity grids. Among the most notable may be those carried out by Panwar et al. [36], who used a real-time resiliency framework for analysis and sizing of energy storage; Mohagheghi and Rebennack [37] who studied a two-stage stochastic and nonlinear optimization model for operating a power grid exposed to a natural disaster; Shahid et al. [38] who, in order to improve the resilience of the microgrids control, a distributed consensus-based control was utilized by spreading an information network across the small distribution grid; Rocchetta and Patelli [39] who proposed a framework for advanced uncertainty quantification and vulnerability assessment of power grids; Barnes et al. [40], who developed a method to evaluate the benefits of networked microgrids for improving resilience; Ilo [41], who presented an architecture for smart grid operations that matches the electricity market rules and the cyber security and privacy requirements; Khomami and Sepasian [42], who proposed a new method for restoration and emergency reaction planning; Hussain et al. [43], who proposed a three-step analysis in order to elaborate the role of microgrids in enhancing the resilience of power systems; Ding et al. [44], who proposed a novel load restoration optimization model to coordinate topology reconfiguration and microgrid formation while satisfying a variety of operational constraints; Lin and Bie [45] who presented a new tri-level defender-attacker-defender model for distribution system; or the investigation

conducted by Mousavizadeh et al. [46], who proposed a linear path-based approach to model the topological characteristics of the network.

However, the solar-plus-storage benefits for end-users placed at radial and network grid segments from an economic and resiliency analysis have not been given the same attention, so a study that addresses them is necessary. From a deep survey of grey literature and updated literature related to the topic addressed here, it was possible to find that—even though there are plenty deal of different approaches—this chapter undoubtedly contributes to the pool of existing knowledge by giving an economic and resiliency analysis of solar-plus-storage benefits for end-users placed at radial and network grid segments (to our knowledge, so far not addressed explicitly in the scientific literature). By performing this thorough literature review, we ensure the originality of the idea and method here presented.

This first section briefly discussed the economic and resiliency benefits of using solar-plus-storage for end-users placed at radial and network grid segments; in the second section, the method used to conduct the research will be exposed; in the third section, case studies on the implementation of solar-plus-storage for end-users placed at radial and network grid segments will be presented and discussed; subsequently, in the fourth section, conclusions will be presented.

2 Material and Methods

In order to carry out the research presented here, three sites with critical infrastructures were selected in which the performance of installations with photovoltaic solar panels and battery storage could be evaluated. Through information available to the general public through the internet and through the use of plausible assumptions, the necessary data were obtained to carry out energy resilience assessments. For each of the three selected critical sites, the economic and resilience benefits of using solar photovoltaic and battery-based systems were modeled. This section documents the information obtained and the assumptions made to carry out the simulations.

Within the set of possible critical infrastructures to be considered, secondary schools, fire stations and residences for the elderly were selected, due to their usual nature.

The selected sites were:

- **Tottenville High School:** 100 Luten Avenue New York City (Staten Island), New York 10,312 [47].

Description and Data of the Loads

Tottenville High School is located on Staten Island and served as a safe haven for the aftermath of Hurricane Sandy [48–52].

Taking into account the high school student body (3856 students), data provided by the U.S. Department of Energy and the New York City Climate Zone (ASHRAE Climate Zone 4A) have estimated annual energy consumption to be 1,883,392 kWh/year.

With respect to the months of May and September, peak loads do not increase during the summer months (late August/early September) due to holiday periods (Fig. 1).

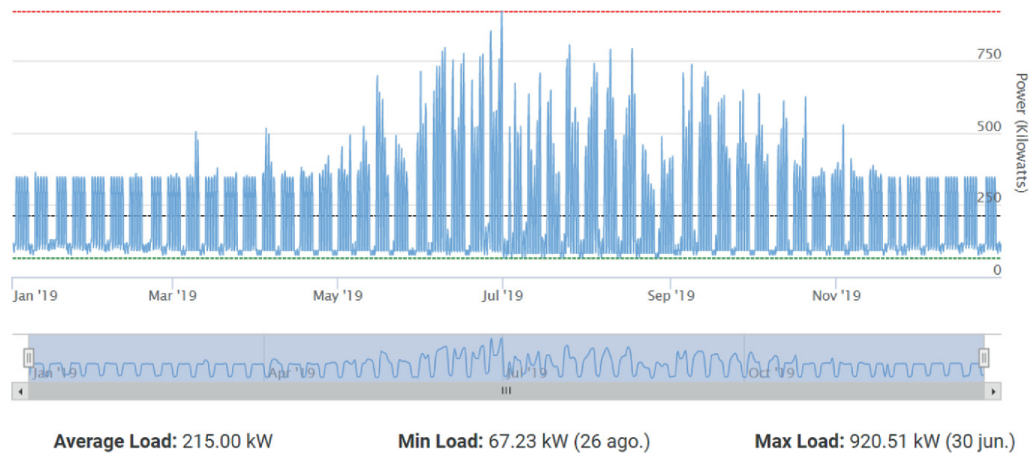


Fig. 1 Tottenville High School estimated annual energy profile.

Source Adapted from ReOpt Lite software

The daily consumption profile for the day of the estimated maximum load (30 June) is shown in Fig. 2. As expected the peak energy consumption takes place during the afternoon.

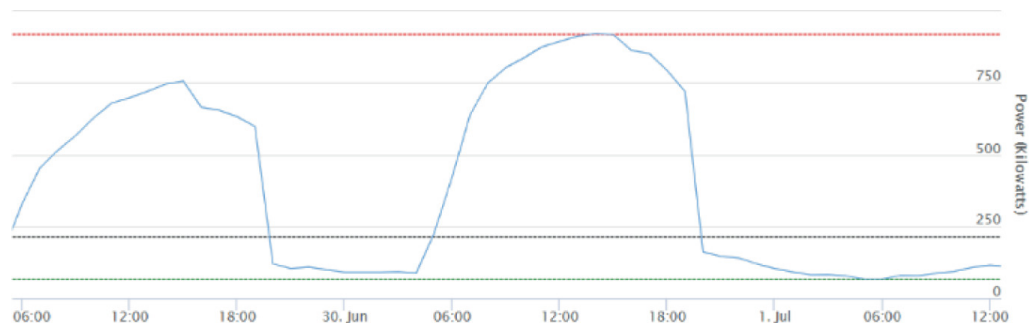


Fig. 2 Tottenville High School estimated daily energy profile for 30th June.

Source Adapted from ReOpt Lite software

Rate Used

Tottenville High School is contracted at SC-9—General Large Low Tension Service [NYC] [53]. The institute of higher education is suitable for a net balance contract. In the absence of first-hand information, it will be assumed that Tottenville High School is a site that has two or more transformers to feed a single customer (spot network), which would require expensive additional equipment for the solar photovoltaic system to export to the power grid. As a consequence, for the analysis carried out in the investigation presented here it will be assumed that a reverse power relay will be used to prevent the export of electricity.

Estimated Critical Load

According to [54], it has been estimated that the critical load of the higher education institute is 10% of the total load.

Backup Power

In the absence of first-hand information, it will be assumed that Tottenville High School does not have diesel generators as backup power.

Evaluation of Photovoltaic Solar Energy

The total area available on the roof of Tottenville High School is 2632 m² (28,300 ft²).

- **43rd Battalion, Engine 245, FDNY Ladder 161:** 2929 West 8th Street (Greenwich Village), New York [55].

Description and Data of the Loads

The 43rd Battalion, Engine 245, FDNY Ladder 161 is located at 2929 West 8th Street in Greenwich Village, and provides firefighting services.

The 43rd Battalion, Engine 245, and Ladder 161 of the FDNY and the NYPD's 60th Precinct share a combined fire and police station built in 1971. The facility is approximately 0.25 mile north of Lower New York Bay and 0.25 mile south of Coney Island Creek [56]. The facility lost functionality during Hurricane Sandy because of significant damage to mechanical, electrical and plumbing equipment. Flood inundation was approximately 5 feet above grade and damaged interior finishes, contents, and equipment throughout the first floor. Floodwater entered the facility through windows, doorways, and ventilation wells, then spread to the basement through stairways, and collapsed the basement wall separating the fire station and police station. The floodwater inundation reached the basement ceiling and damaged the MEP equipment (furnace, hot water heater, switchgear, etc.) for both stations. Although the police station generator was on the first floor, the transfer switch was located in the lower basement and was inundated. Both the FDNY and NYPD evacuated most vehicles prior to and during Sandy to prevent damage, but most equipment within the stations was destroyed [56]. 45 days after Sandy, the FDNY was operating from the station on generator power. The fuel service station was still inoperable because they lacked power to pump fuel to vehicles. The NYPD was running limited operations from a command trailer adjacent to the building with most personnel relocated to an adjacent precinct's facility. Telecommunications equipment that had been located on the first floor prior to Hurricane Sandy was being elevated to the second floor [56].

Taking into account that fire stations are not one of the types of commercial reference buildings provided by the United States Department of Energy, this load has been assimilated to that of an apartment located in a low-rise building (to represent firefighter accommodation). For its part, and taking into account the climate zone of New York City (ASHRAE climate zone 4A), it has been estimated that annual energy consumption is 42,530 kWh/year.

The estimated annual energy profile of the secondary school is shown in Fig. 3.

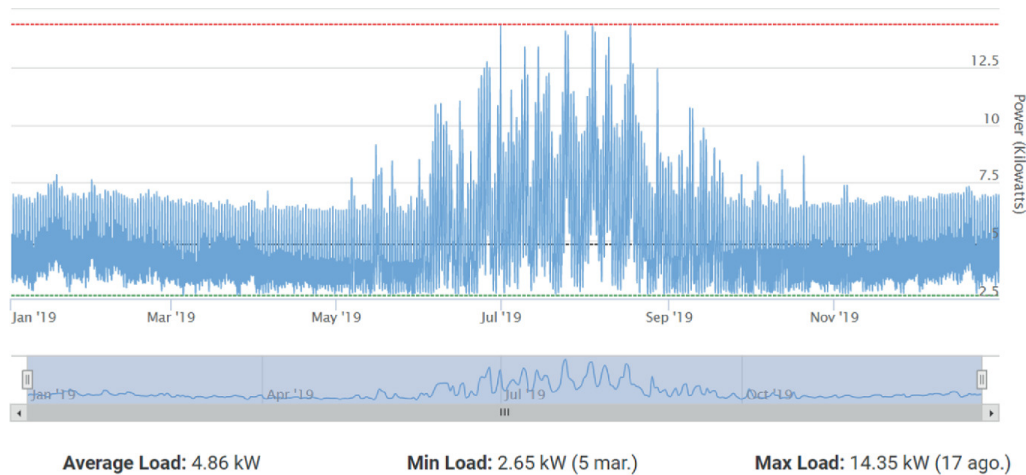


Fig. 3 43rd Battalion, Engine 245, FDNY Ladder 161 estimated annual energy profile.

Source Adapted from ReOpt Lite software and from [57]

The daily consumption profile for the day of the estimated maximum load (August 17) is shown in Fig. 4. As expected the peak energy consumption takes place during the afternoon.

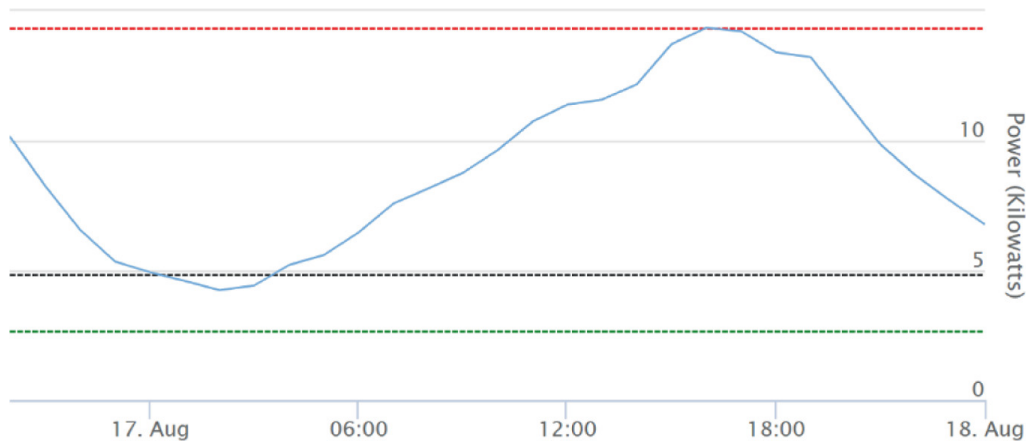


Fig. 4 43rd Battalion, Engine 245, FDNY Ladder 161 estimated daily energy profile for 17th August.

Source Adapted from ReOpt Lite software

Rate Used

The 43rd Battalion, Engine 245, FDNY Ladder 161 has contracted the SC-9—General Large Low Tension Service [NYC] [53] rate. The fire station is ideal for a net balancing contract. It will be assumed that the 43rd Battalion, Engine 245, FDNY Ladder 161 is located on a radial network.

Estimated Critical Load

Based on [57, 58] it has been estimated that the critical load of the fire station is 50% of the total load. These charges would include lighting charges, computers, telecommunications equipment, and pumps to fill trucks with fuel.

Backup Power

It will be assumed that the 43rd Battalion, Engine 245, FDNY Ladder 161 does not currently have any backup power.

Evaluation of Photovoltaic Solar Energy

The total area available on the roof of the 43rd Battalion, Engine 245, FDNY Ladder 161 is 485 m² (5210 ft²).

- **Brighton/Manhattan Beach Senior Center** 60 West End Avenue Brooklyn (Brooklyn), New York 11,235 [59].

Description and Data of the Loads

El Brighton/Manhattan Beach Senior Center está localizado en 60 West End Avenue Brooklyn, NY 11,235. Hurricane Sandy left the senior center without power or heat from October 29, 2012 until January 2013 [60]. El Brighton/Manhattan Beach Senior Center está considerado por el Estado de Nueva York como un “high risk area” [61].

Considering that the Brighton/Manhattan Beach Senior Center has 148 residents [62], data provided by the U.S. Department of Energy (it has been assumed that the demand for a senior center can be assimilated to that of a midrise apartment) and the New York City climate zone (ASHRAE climate zone 4A) have estimated that annual energy consumption is 564,896 kWh/year.

The estimated annual energy profile of the senior center is shown in Fig. 5.

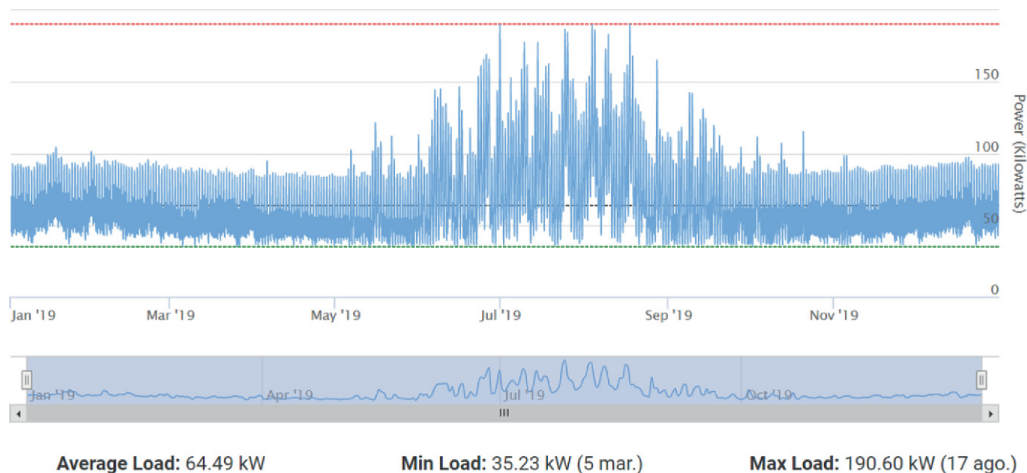


Fig. 5 Brighton/Manhattan Beach Senior Center estimated annual energy profile.

Source Adapted from ReOpt Lite software

The daily consumption profile for the day of the estimated maximum load (August 17) is shown in Fig. 6. As expected the peak energy consumption takes

place during the afternoon.

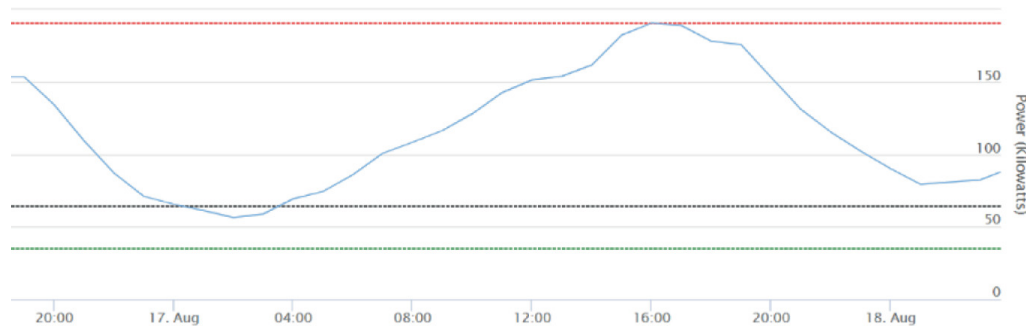


Fig. 6 Brighton/Manhattan Beach Senior Center estimated daily energy profile for 17th August.
Source Adapted from ReOpt Lite software

Rate Used

The Brighton/Manhattan Beach Senior Center has contracted the SC 8—Multiple Dwellings Redistribution TOD Service [NYC] [63] rate.

El Brighton/Manhattan Beach Senior Center is suitable for a net balance contract. The Brighton/Manhattan Beach Senior Center is connected to a secondary network system with geographically separated network units and the network-side terminals of the network protectors interconnected by low-voltage cables that span the distance between sites. In this case the low-voltage cable circuits of the grid networks are supplied by numerous network units (i.e., the senior center is connected to an “area network”) [64].

Estimated Critical Load

Based on [57] it has been estimated that the critical load of the fire station is 40% of the total load.

Backup Power

It will be assumed that the Brighton/Manhattan Beach Senior Center does not currently have any back-up power.

Evaluation of Photovoltaic Solar Energy

The total area available on the roof of the Brighton/Manhattan Beach Senior Center is 1650 m² (17,760 ft²).

2.1 Description of Modeling and Assumptions

The REopt™ Lite web tool helps commercial building managers [65]:

- Evaluate the economic viability of grid-connected PV, wind, and battery storage at a site
- Identify system sizes and battery dispatch strategies to minimize energy costs
- Estimate how long a system can sustain critical load during a grid outage.

Formulated as a mixed integer linear program, REopt recommends an optimally sized mix of renewable energy, conventional generation, and energy storage technologies; estimates the net present value of implementing those technologies; and provides a dispatch strategy for operating the technology mix at maximum economic efficiency [66].

REopt is a time series model in which energy balances are ensured at each time step (often in 15-min or 1-h intervals) and operational constraints are upheld while minimizing the cost of energy services for a given customer [67]. The typical time step (and the one used for the analysis here conducted) is 1 h, resulting in 8760 time steps in a typical N-year analysis [67]. This approach ensures that seasonal variation in load and resource availability is captured [67].

Appendix 1 summarizes the modeling assumptions used for each site.

2.2 Economic Evaluation of Resilience

The investments made by customers with the aim of reducing their vulnerabilities to problems related to electrical reliability are, on the one hand, difficult to find [68] and, on the other hand, difficult to “reconcile” by using data from sources using different user classification systems [68]. Certainly economic estimates of the cost of unserved energy are generally limited, poorly documented or based on questionable assumptions [69]. Finally, to mention that there is very little information available in the public domain regarding the costs of energy quality problems (an increasingly important aspect of service reliability) [69].

In theory, and from an economic perspective, the desire to pay and the desire to accept measures to improve electrical reliability should produce the same value for a given interruption [69]. In practice, it is difficult to formulate questions leading to identical results [69]. As Sullivan et al. [69] have found, the desire to accept measures produces an estimated value greater than the desire to pay for such measures. The problem of evaluating resilience from an “electrical” perspective has resulted in most of the schemes based on photovoltaic solar energy and electrochemical storage connected to the conventional electricity grid having been designed taking into account a number of scenarios in which only different interest rates and electricity tariffs are considered (without taking into account aspects such as electrical resilience) [70].

The research presented here provides, through the REopt model, a monetary value for electrical resilience in order to evidence its impact on the design of the scheme and on the economics of the project. According to Anderson et al. [71], the monetary value of electrical resilience will be equal to the reduction in the cost of the electrical disturbance that a hybrid system based on renewable energies would provide. The cost of power outages depends, among other things, on the number of users, the frequency of events and the vulnerability of users to them [72].

In the event that a hurricane affects critical infrastructure, it is possible for the following to occur cascading second-, third-, and fourth-tier effects stemming from the loss of power (for example in September 2017, Hurricane Irma caused significant damage to Puerto Rico; in this case water pumps shut

off and water testing labs were affected, causing further delays in accessing safe, potable water) [73].

There are two different ways of quantifying power failure costs: the macroscopic method and the microscopic method [74]. The macroscopic method of assessing energy security would be to use the costs of unsupplied energy [\$/kWh] and/or the cost per unit of interrupted power [\$/kW] as a measure of the severity of the interruption [74]. This perspective aims at assessing the costs of interrupted power at national level by estimating the total cost of interruptions over a long period of time (e.g. 1 year) [74].

In this case and due to the large amount of data handled, it is difficult to evaluate precisely the value of the energy not served for each user [74]. The microscopic method uses the costs of unsatisfied energy and requires large-scale surveys to collect information on the cost of the power outage [74]. Power outage costs are a function of the blackout and its impact on the user, and can be presented as a function of the duration of the blackout [74]. In this case the damage caused by the blackout will depend on the type of user who has not been satisfied with the required electricity, the duration of the blackout, and the situation in which the electricity supply interruption occurs (day of the week, time of day, activity of the customer at the time of the interruption, etc.) [74].

In order to determine the resilience value of the facilities evaluated in the research presented here, the macroscopic method was chosen. This is because it is widely applicable and replicable at other facilities and could be applied without the need for lengthy data collection activities at the facility in question. In order to calculate blackout costs, the Interruption Cost Estimator (ICE) [75] was used to represent the value of electrical resilience at each site (using metrics relating to electrical reliability and the characteristics of these sites).

The Interruption Cost Estimator (ICE) needs several inputs to estimate the costs of individual interruptions depending on the type of user [76]. The Interruption Cost Estimator (ICE) takes into account, among others, average household income, annual electricity consumption, the average duration of an individual interruption, or reliability indices such as the Customer Average Interruption Duration Index (CAIDI) [76].

Since 2005, the Department of Public Service of the New York State has published an annual report on the reliability of electric service [77]. The Public Service Commission relies primarily on two commonly used industry metrics to assess performance relative to reliability: the System Average Interruption Frequency Index (SAIFI) and the Customer Average Interruption Duration Index (CAIDI or duration) [77]. As can be seen in Tables 1, 2, and 3, these values (SAIFI and CAIDI) were generally the highest in the last 5 years by 2018.

Table 1 Con Edison system-wide reliability excluding major storms for network grids

With edison (network)	2014	2015	2016	2017	2018	5 years average
Number of interruptions	10,080	10,523	6980	9462	9187	9246
Number of customer-hours	543,158	569,966	348,053	441,055	434,540	467,354
Number of customers affected	63,013	67,966	46,918	62,005	59,620	58,904
Number of customers served	2,473,101	2,497,705	2,510,320	25,453,512	2,568,843	2,519,064

With edison (network)	2014	2015	2016	2017	2018	5 years average
Average duration per customer affected (CAIDI)	8.62	8.39	7.42	7.11	7.29	7.77
Average duration per customers served	0.22	0.23	0.14	0.18	0.17	0.19
Interruptions per 1000 customers served	4.10	4.25	2.79	3.77	3.61	3.70
Number of customers affected per customer served (SAIFI)	0.03	0.03	0.02	0.02	0.02	0.02

Source Electric Distribution Systems [77]

Table 2 Con Edison system-wide reliability including major storms for radial grids

With edison (radial)	2014	2015	2016	2017	2018	5 years average
Number of interruptions	6347	6222	7224	6738	14,398	8184
Number of customer-hours	614,218	621,073	882,602	737,947	11,171,045	2,805,377
Number of customers affected	311,015	311,190	413,417	343,915	622,467	400,401
Number of customers served	889,094	887,471	899,852	889,546	896,116	892,416
Average duration per customer affected (CAIDI)	1.97	2.00	2.13	2.15	17.95	5.24
Average duration per customers served	0.69	0.70	0.99	0.82	12.56	3.15
Interruptions per 1000 customers served	7.15	7.00	8.14	7.49	16.18	9.19
Number of customers affected per customer served (SAIFI)	0.35	0.35	0.47	0.38	0.70	0.45

Source Electric Distribution Systems [77]

Table 3 Con Edison system-wide reliability excluding major storms for radial grids

With edison (radial)	2014	2015	2016	2017	2018	5 years average
Number of interruptions	5957	5943	6764	6148	7470	6456
Number of customer-hours	545,339	604,408	726,044	610,945	710,418	639,431
Number of customers affected	297,041	309,669	383,891	317,422	356,896	332,984
Number of customers served	889,094	887,471	899,852	889,546	896,118	892,416
Average duration per customer affected (CAIDI)	1.84	1.95	1.89	1.92	1.99	1.92
Average duration per customers served	0.61	0.68	0.82	0.68	0.80	0.72
Interruptions per 1000 customers served	6.71	6.68	7.62	6.83	8.40	7.25
Number of customers affected per customer served (SAIFI)	0.33	0.35	0.43	0.35	0.40	0.37

Source Electric Distribution Systems [77]

The frequency of blackouts (SAIFI) depends on whether the installation in question is in a meshed network or in a radial network. These values are summarized in Table 4.

Table 4 Con Edison five-year average SAIFI values for radial and network customers

Grid segment	Number of customers affected per customer served (SAIFI)
Radial	0.45
Network	0.02

Source Electric Distribution Systems [77]

Table 5 shows two different values for the Customer Average Interruption Duration Index (CAIDI): “including major storms” and “excluding major storms” (referenced in the technical analysis scenario respectively as “long-term” and “short-term” scenarios). This procedure imposes an upper and lower limit for the duration of blackouts for both meshed and radial networks, and establishes cases of short and long duration for the scenarios analyzed. As can be seen in [78], CAIDI for 2012 (the year of Hurricane Sandy) was 71.91. For this reason and in order to deal with the possibility of repeating circumstances similar to those of 2012, it has been considered appropriate to assume a CAIDI of at least 16.00 h/year for meshed networks within the “long” analysis scenario (with storms).

Table 5 Con Edison CAIDI values for radial and networks customers

Grid type	CAIDI (h/year)	Technical analysis scenario
<i>Radial</i>		
Average duration per customer affected excluding major storms (5 years average)	1.92	Shorts
Average duration per customer affected including major storms (assumption taking into account the most restrictive year in the last 5 years, 2018)	16.00	Long
<i>Network</i>		
Average duration per customer affected excluding major storms (5 years average)	7.77	Shorts
Average duration per customer affected including major storms (assumption taking into account, apart from the last 5 years, 2012 and Hurricane Sandy)	16.00	Long

Source Electric Distribution Systems [77]

The specific costs of interruptions (i.e. the annual value of resilience) were developed using the Interruption Cost Estimator (ICE) [75]. Using the metrics shown in Tables 4 and 5, a table is developed for each of the facilities evaluated. The Unit Cost of Interruption is averaged over the 16 h that the Interruption Cost Estimator is able to analyze to provide an average cost of interruption.

Table 6 summarizes the hourly costs of interruptions, or the value provided by resilience, for the facilities included in the study.

Table 6 Value of resiliency for study facilities

Site	Short technical analysis scenario			Total cost (2016\$)	Long technical analysis scenario			Total cost (2016\$)
	Cost per event (2016\$)	Cost per average kW (2016\$)	Cost per unserved kWh (2016\$)		Value of resiliency provided (\$/h/year)	Cost per average kW (2016\$)	Cost per unserved kWh (2016\$)	
Tottenville high school (network)	\$4976.00	\$1443.37	\$185.76	\$99.52	\$9893.67	\$2869.82	\$179.36	\$197.87
43rd Battalion, engine 245, FDNY Ladder 161 (radial)	\$1050.49	\$304.71	\$158.70	\$21.01	\$9893.67	\$2869.82	\$179.36	\$4452.15
Brighton/Manhattan Beach senior center (network)	\$4976.00	\$1443.37	\$185.76	\$99.52	\$9893.67	\$2869.82	\$179.36	\$197.87

Source Adapted from [75]

The REopt model was used to dimension schemes based on photovoltaic solar energy, batteries and/or diesel groups for four different scenarios, evaluating both economic and resilience benefits:

1. Scenario 1: Dimensioning of the Photovoltaic Solar System from an Economic Perspective.

The model selects the solar and storage resources that are profitable for the installation while it is connected to the electricity grid, and then evaluates the economic benefits that these schemes provide to the system.

2. Scenario 2: Sizing of the Photovoltaic Solar Facility to Meet Electrical Resilience Needs.

The model selects the solar and storage resources needed to dimension schemes based on photovoltaic solar energy that are capable of sustaining critical electrical loads during short and long term blackouts; to then evaluate the economic benefits that these systems can provide during the normal operation of the electrical grid.

3. Scenario 3: Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience.

The model selects solar resources, storage, and diesel groups to design systems capable of maintaining critical loads during short and long term blackouts; to then evaluate the economic benefits that these systems can provide during normal grid operation.

4. Scenario 4: Dimensioning of the Scheme Assuming a System Based Exclusively on a Diesel Group to Meet Electrical Resilience Needs.

The model dimensions a diesel group capable of maintaining critical loads during short and long term blackouts.

For the analysis carried out in the research presented here, a scheme will be profitable if it has a net present value equal to or greater than zero and therefore provides a saving to the useful life cost of the project. In this sense, the schemes are selected in order to maximize savings over the life of the project.

In each scenario where a photovoltaic solar installation is included to satisfy the needs of electrical resilience, the scheme was able to operate in order to improve the economic results of the same both during an operation connected to the electrical grid and to feed critical loads during blackouts. Scenario 1 was modeled with no value assigned to resilience. For scenarios 2–4, they were modelled with two different blackout durations (a “short” duration and a “long” duration blackout, as shown in Table 5) in order to demonstrate how the dimensions of the scheme and its economy vary with blackout durations.

Because solar resource and critical loads are both variable over time, sizing a photovoltaic solar-based scheme to meet electrical resilience needs will vary depending on when the blackout begins. In this sense, to adequately take into account the stochastic nature of the critical load and the solar resource, the model should be simulated several times with the blackout starting at different times of the year. Therefore, the largest scheme required to maintain the critical load during the different simulations of the scheme would represent the worst case, and it can be assumed that it satisfies the critical load at any time. Due to the computational complexity of the model, for the purposes of this analysis the worst blackout will be assumed to occur during the period with the highest load and the lowest solar generation.

For the analysis performed, it will be assumed that the battery is fully charged when the blackout occurs. Some blackouts due to extreme weather conditions may be predicted so the building owner may choose to charge the battery before the blackout occurs. However, some blackouts cannot be predicted so in this case the assumption that the battery is fully charged is optimistic. A more detailed stochastic assessment of the impact of the state of charge of the battery is not within the scope of the analysis of the research presented here.

It will also be assumed that the battery will have to be replaced once throughout the 25-year project life cycle, and that the cost of replacement is amortized through the initial capital cost. The number of cycles to the end of the battery life varies depending on the depth of discharge [79]. On the other hand, the useful life of a lithium ion battery can reach 12 years at a temperature of 25 °C and with a limited cycle of discharge depth [80].

Each scenario is described in more detail below:

1. Scenario 1: Dimensioning of the Photovoltaic Solar Installation from an Economic Perspective.

In the first scenario, resilience is not included as a design constraint. In this case the optimal system configuration is based on achieving the lowest life cycle

cost assuming that the power grid is always available. In scenario 1.1 the revenues from the scheme are grid savings, incentives and tax exemptions.

2. Scenario 2: Sizing of the Photovoltaic Solar Facility to Meet Electrical Resilience Needs.

In the second scenario, resilience is introduced as a design constraint. Instead of designing the scheme exclusively to maximize the results of acquiring a smaller amount of energy and obtaining a series of incentives related to the energy policy of the place, we now impose that the model be able to identify a system that can support the critical load during a specified duration of the blackout. Although the system is specifically designed to satisfy a number of loads during the specified blackouts, it can also be used for economic gain in normal operation, as was the case in the first scenario. This scenario shows the extra cost required by adding resilience as a design constraint as well as the extra benefit of avoiding the costs associated with blackouts. In this scenario, two blackout durations (short and long) are evaluated, and each is evaluated by assigning and not assigning a value to resilience.

Once the optimal sizes of the scheme based on solar photovoltaic and/or electrochemical storage were determined based on economic benefits, a number of simulations were carried out in order to evaluate the benefits of added resilience. The total time during which the critical load could be sustained varied depending on the state of charge of the battery, the solar resource, and the size of the critical load during the blackout. For the analysis carried out here, the “worst case” in which a blackout can occur throughout the year was evaluated. This aims to show the minimum amount of resilience that the system is expected to provide (the worst case was the period with the highest load and the lowest solar generation).

3. Scenario 3: Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience.

The third of the scenarios is essentially the same as the second with the exception that the possible technologies to choose now include, apart from photovoltaic solar panels and electrochemical batteries, diesel generators. In this case, the model limits the operation of the diesel group only during blackouts (photovoltaic solar panels and electrochemical batteries can operate both during blackouts and when the conventional electricity grid is operational).

4. Scenario 4: Dimensioning of the Scheme Assuming a System Based Exclusively on a Diesel Group to Meet Electrical Resilience Needs.

The fourth scenario considers only diesel groups as a candidate technology. The generators in this analysis are unable to participate in demand response due to the small size of the schemes and the complexity of operating a diesel group to

participate in demand response. Scenario 4 is included to provide an overview of the various options available to ensure the resilience of the facility.

The scenarios are summarized in Table 7.

Table 7 Scenarios evaluated

Scenario	Description	Duration of the blackout	Economic evaluation of resilience
1.1	Dimensioning of the photovoltaic solar installation from an economic perspective (no requirement is imposed regarding the resilience of the system)	Not available	No
2.1.a	Dimensioning of the photovoltaic solar installation to meet the needs of electrical resilience	Short	No
2.1.b	Dimensioning of the photovoltaic solar installation to meet the needs of electrical resilience	Short	Yes
2.2.a	Dimensioning of the photovoltaic solar installation to meet the needs of electrical resilience	Long	No
2.2.b	Dimensioning of the photovoltaic solar installation to meet the needs of electrical resilience	Long	Yes
3.1.a	Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience	Short	No
3.1.b	Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience	Short	Yes
3.2.a	Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience	Long	No
3.2.b	Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience	Long	Yes
4.1.a	Dimensioning of the scheme assuming a system based exclusively on a diesel group to meet the needs of electrical resilience	Short	No
4.1.b	Dimensioning of the scheme assuming a system based exclusively on a diesel group to meet the needs of electrical resilience	Short	Yes
4.2.a	Dimensioning of the scheme assuming a system based exclusively on a diesel group to meet the needs of electrical resilience	Long	No
4.2.b	Dimensioning of the scheme assuming a system based exclusively on a diesel group to meet the needs of electrical resilience	Long	Yes

Source Own elaboration

Although natural gas generators, co-generators and other distributed generators may also offer economic and resilience benefits, they were not modeled because they are outside the scope of the research presented here.

3 Results and Discussion

This section provides a summary of the four scenarios assessed for the three sites.

3.1 Tottenville High School

1. **Scenario 1: Dimensioning of the photovoltaic solar installation from an economic perspective (no requirement is imposed regarding the resilience of the system).**

Table 8 presents a summary of the size and present value of a number of future cash flows arising from an investment for Scenario 1.

Table 8 Results for Tottenville high school scenario 1

Tottenville high school	
Scenario 1: scheme based on a photovoltaic solar installation and electrochemical storage from an economic perspective	
	System 1.1: No value is included for resilience
Size of solar photovoltaic system (kW-DC)	108 kW
Electrochemical battery size (kWh)	170 kWh
Electrochemical battery size (kW)	58 kW
Net present value	\$62,728

Source Own elaboration

System 1.1 is a traditional economic analysis that places no value on resilience. This scheme would have, for Tottenville High School, a net present value of \$62,700 over 25 years.

For case 1.1 savings were obtained through demand management during peak demand periods. This fact is shown in Fig. 7 where you can see how the battery is strategically discharged to reduce peak loads.

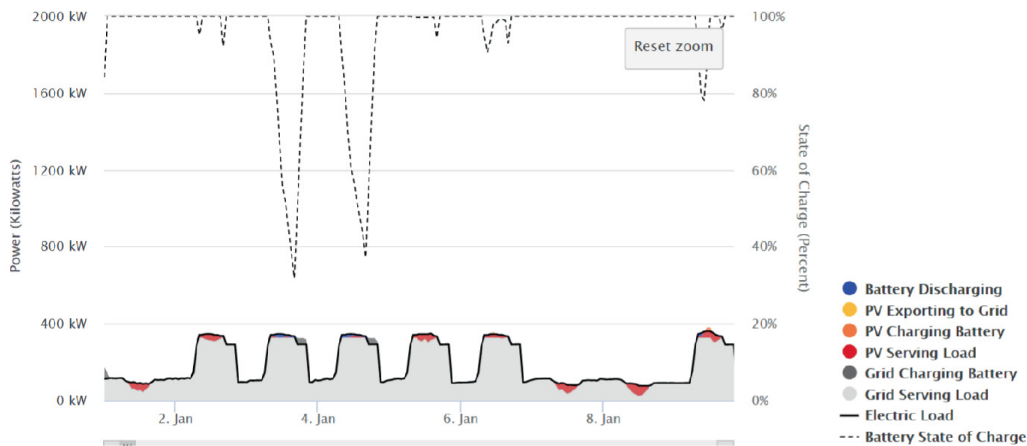


Fig. 7 Combination of use of photovoltaic solar energy and electrochemical storage to reduce peak demand.

Source Adapted from ReOpt Lite software

It will be assumed that Tottenville High School is a site that has two or more transformers to feed a single customer (spot network), which could be problematic to export energy. As a result, the savings resulting from net metering will not be taken into account in the analysis. In this case it can be assumed that a reverse power relay could be installed to avoid exporting. Another alternative would be for Tottenville High School to implement a smart grid-based solution that would allow for the export of electric power. However, the estimated cost of installing a smart grid is often considerably more expensive than the potential benefit to be gained as a result of the exported power of the photovoltaic solar panels over the 25 years of the project's useful life. As a consequence, the installation of a reverse power relay would be a better option from an economic point of view.

It should also be mentioned that batteries could be used for peak demand management while also assigning a percentage of the capacity (in Ah) of the batteries to the “demand response”. Optimizing the use of batteries to simultaneously manage peak demand and demand response requires detailed modeling. In this sense, the research presented here will assume that the battery will be used for peak demand management rather than for demand response (this is because peak demand management will provide higher revenues).

2. Scenario 2: Sizing of the Photovoltaic Solar Facility to Meet Electrical Resilience Needs

Table 9 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 2.

Table 9 Results for Tottenville high school scenario 2

Tottenville high school				
Scenario 2: sizing of the photovoltaic solar installation + electrochemical batteries to meet electrical resilience needs				
	System 2.1A: short blackout; no resilience value included (\$0 per kWh)	System 2.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 2.2A: long blackout; no resilience value included (\$0 per kWh)	System 2.2B: Long blackout; resilience is assigned a value (\$100 per kWh)
Size of solar photovoltaic system (kW-DC)	108 kW	108 kW	108 kW	108 kW
Electrochemical battery size (kWh)	567 kWh	567 kWh	664 kWh	664 kWh
Electrochemical battery size (kW)	109 kW	109 kW	119 kW	119 kW
Net present value before microgrid investment	\$18,902	\$18,902	\$3838	\$3838
Avoided outage costs	\$0	\$147,253	\$0	\$177,546
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$100,654	\$126,303	\$40,541	\$137,005

Source Own elaboration

The dispatch strategy optimized by REopt Lite for the specified outage period as well as the rest of the year for System 2.1 and 2.2 is shown in Appendix 2. Below we evaluate the length of time that a scheme based on a 108 kW solar photovoltaic installation and a battery system of (2.1) 109 kW/567 kWh; (2.2) 119 kW/664 kWh could sustain critical load during a “short” blackout of 7.77 h and a “long” blackout of 16 h. For the “short” blackout, for the worst case scenario (low solar irradiation and high demand), the system could feed the critical load during the 7.77 h assigned to this type of blackout (see Fig. 17), or at 50.41% of the critical load during 57 h. For the “long” blackout, for the worst case scenario (low irradiation and high demand), the scheme could feed the critical load in its entirety for 16 h (see Fig. 18), or 50.14% of the critical load for 71 h; see Table 10.

Table 10 Percentage of critical load the system can feed

	System 2.1B: short-term resilience is assigned a value	System 2.2B: long-term resilience is assigned a value
7.77-h blackout (worst case)	100%	/
16-h blackout (worst case)	/	100%
57-h blackout	50.41%	/
71-h blackout	/	50.14%

Source Own elaboration

Although photovoltaic solar panels provide some energy, the battery provides most of the energy needed to meet critical loads (see Figs. 15 and 16). The net present value for Systems 2.1B is greater than 2.1A; while System 2.2B is greater than 2.1A; see Table 8—this again demonstrates the fact that assigning a value to resilience has an impact on grid users.

3. Scenario 3: Dimensioning of the Scheme Assuming a Hybrid System Based on Solar Energy and a Diesel Group to Meet the Needs of Electrical Resilience.

Table 11 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 3.

Table 11 Results for Tottenville high school scenario 3

Tottenville high school				
Scenario 3: dimensioning of the photovoltaic solar installation + electrochemical storage + diesel group to meet electrical resilience needs				
	System 3.1A: short blackout; no resilience value included (\$0 per kWh)	System 3.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 3.2A: long blackout; no resilience value included (\$0 per kWh)	System 3.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Size of solar photovoltaic system (kW-DC)	108	108	108	108
Electrochemical battery size (kWh)	512	512	270	270
Electrochemical battery size (kW)	102	102	70	70
Diesel generator size (kW)	14	14	51	51
Diesel generator fuel used (L)	30	30	106	106
Net present value before microgrid investment	\$27,105	\$27,105	\$30,716	\$30,716
Avoided outage costs	\$0	\$149,575	\$0	\$208,466
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-10,848	\$138,727	\$2779	\$283,245

Source Own elaboration

Scenario 3 demonstrates that, with the exception of System 3.1A, all schemes are economically advantageous. By integrating a diesel generator into the scheme consisting of photovoltaic solar panels and electrochemical batteries, the scheme can cope with a longer-lasting blackout at a much lower cost than would be incurred if the scheme were composed solely of a photovoltaic system and batteries. Depending on the length of the outage for which the system is designed and whether (or not) resilience is assigned a value, Tottenville High School could save between \$10,848 and \$283,245 over the system's 25-year lifespan. Assessing the economic value of resilience increases the net present value, especially in the long duration blackout scenario (3.2B).

Despite the fact that the size of the photovoltaic system remains at 108 kW for all systems evaluated, the capacity of the batteries decreases and that of the generating set increases when the blackout goes from “short” to “long”. This is because a much larger battery would be required to cope with a long blackout. In this sense peak demand management provides diminishing benefits and the savings from battery charge management do not outweigh the costs of a larger battery. Note that photovoltaic solar panels and batteries allow a smaller diesel group to cover the critical load (Fig. 8). Finally comment that the capital cost for systems designed to be able to cope with short term blackouts is slightly higher than those designed to be able to cope with long term blackouts due to

the larger size of the batteries; however, the payback time for the latter is shorter.

4. Scenario 4: Dimensioning of the Scheme Assuming a System Based Exclusively on a Diesel Group to Meet Electrical Resilience Needs.

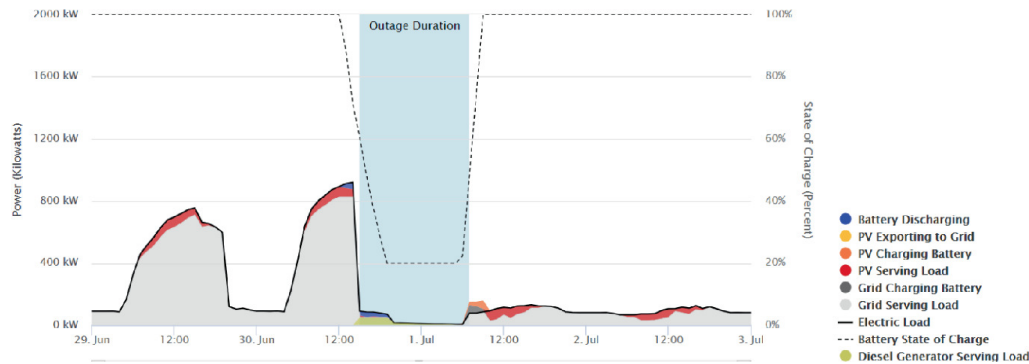


Fig. 8 Combination of use of photovoltaic solar energy, electrochemical storage and a diesel group to cope with the critical load during a 16-h blackout (“long” blackout).

Source Adapted from ReOpt Lite software

Table 12 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 4.

Table 12 Results for Tottenville high school scenario 3

Tottenville high school				
Scenario 4: dimensioning of the scheme assuming a system based exclusively on a diesel group to meet electrical resilience needs				
	System 4.1A: short blackout; no resilience value included (\$0 per kWh)	System 4.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 4.2A: long blackout; no resilience value included (\$0 per kWh)	System 4.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Diesel group size (kW)	92	92	92	92
Diesel generator fuel used (L)	128	128	155	155
Net present value before microgrid investment	\$-55,792	\$-55,792	\$-55,988	\$-55,988
Avoided outage costs	\$0	\$50,933	\$0	\$58,523
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-60,377	\$-9443	\$-60,573	\$-2050

Source Own elaboration

As can be seen, the net present value for all systems in Scenario 4 where a value is assigned to resilience is negative. The nominal power of the diesel

group does not remain constant when blackouts change from short to long duration.

3.2 Discussion of Tottenville High School Results for All Scenarios

Table 13 compares the net present value for the three scenarios (2–4) that dimension the schemes based on their resilience. Through Table 13 it can be seen that scenario 3 has the highest net present value for long term blackouts. Scenario 4 has a negative net present value.

Table 13 Comparison of net present value and simple payback for Tottenville high school scenarios 2, 3, and 4

Tottenville high school				
More cost-effective option for dealing with blackouts				
	Short blackout; no resilience value included (\$0 per kWh)	Short blackout; resilience is assigned a value (\$100 per kWh)	Long blackout; no resilience value included (\$0 per kWh)	Long blackout; resilience is assigned a value (\$100 per kWh)
Scenario 2: photovoltaic solar energy + Electrochemical storage Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$100,654	\$126,303	\$40,541	\$137,005
Scenario 3: photovoltaic solar energy + Electrochemical storage + diesel group Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$−10,848	\$138,727	\$2779	\$283,245
Scenario 4: diesel group Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$0	\$−9443	\$0	\$−2050

Source Own elaboration

3.3 43rd Battalion, Engine 245, FDNY Ladder 161

1. **Scenario 1: Dimensioning of the photovoltaic solar installation from an economic perspective (although no requirement is imposed regarding the resilience of the system, it is evaluated).**

An overview of the dimensions and costs for Scenario 1 is presented in Table 14.

Table 14 Results for scenario 1 of the 43rd Battalion, engine 245, FDNY ladder 161

43rd Battalion, engine 245, FDNY ladder 161	
Scenario 1: scheme based on a photovoltaic solar installation and electrochemical storage from an economic perspective	
	System 1.1: no value is included for resilience
Size of solar photovoltaic system (kW-DC)	0 kW
Electrochemical battery size (kWh)	9 kWh
Electrochemical battery size (kW)	2 kW
Net present value	\$1867

Source Own elaboration

System 1.1 is a traditional economic analysis that places no value on resilience. This scheme would save the 43rd Battalion, Engine 245, FDNY Ladder 161 \$1867 over 25 years of the project life cycle. In this case, savings were obtained through demand management during peak demand periods. This fact is shown in Fig. 9 where you can see how the battery is strategically discharged to reduce peak loads.

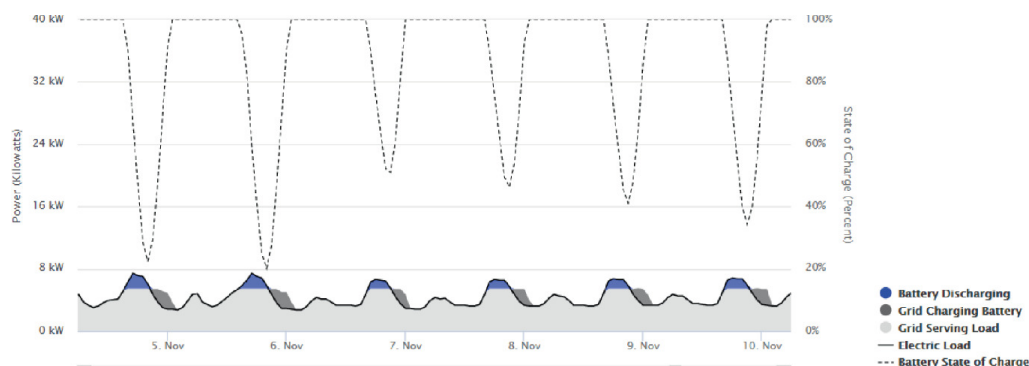


Fig. 9 Using electrochemical storage to reduce peak demand in the 43rd Battalion, Engine 245, FDNY Ladder 161.

Source Adapted from ReOpt Lite software

We then evaluate the length of time that a battery system-based scheme could sustain critical charge during a “short” blackout of 1.92 h and a “long” blackout of 16 h. Because this scenario is designed exclusively from an economic perspective and because the battery system is relatively small compared to charging, batteries are not always capable of satisfying the critical charge in its entirety. For the “short” blackout, for the worst case scenario (low solar irradiation and high demand), the system could supply 87.12% of the critical load for 2 h (see Fig. 20). For the “long” blackout, for the worst case scenario (low irradiation and high demand), the scheme could feed 0% of the critical load for 16 h (see Fig. 20). The 1.3 system could satisfy 46.85% of the critical load for a 5-h blackout; see Table 15.

Table 15 Percentage of critical load that the system can feed

	System 1.1: no value is included for resilience (%)
1.92-h blackout (worst case)	87.12
16-h blackout (worst case)	0

	System 1.1: no value is included for resilience (%)
5-h blackout	46.85

Source Own elaboration

2. Scenario 2: Sizing of the Photovoltaic Solar Facility to Meet Electrical Resilience Needs.

Table 16 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 2.

Table 16 Results for Scenario 2 of the 43rd Battalion, engine 245, FDNY Ladder 161

43rd Battalion, engine 245, FDNY ladder 161				
Scenario 2: sizing of the photovoltaic solar installation + electrochemical batteries to meet electrical resilience needs				
	System 2.1A: short blackout; no resilience value included (\$0 per kWh)	System 2.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 2.2A: long blackout; no resilience value included (\$0 per kWh)	System 2.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Size of solar photovoltaic system (kW-DC)	0 kW	0 kW	4 kW	4 kW
Electrochemical battery size (kWh)	19 kWh	19 kWh	89 kWh	89 kWh
Electrochemical battery size (kW)	7 kW	7 kW	7 kW	7 kW
Net present value before microgrid investment	\$-3403	\$-3403	\$-28,684	\$-28,684
Avoided outage costs	\$0	\$1622	\$0	\$8470
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-4689	\$-3067	\$-32,996	\$-24,526

Source Own elaboration

Scenario 2 shows a system based on photovoltaic solar energy and electrochemical batteries in which no value is assigned to resilience (2.1A and 2.2A) and a value is assigned to resilience (2.1B and 2.2B). Without assigning any value to resilience, a system sized to meet a short-term blackout would have a net present value after microgrid upgrade cost (10% of system capital cost) and benefits of \$-4689 (system 2.1A) and no photovoltaic solar panel would have to be installed.

The impact of assigning a value to resilience is most clearly appreciated when systems are forced to satisfy a long-lasting blackout. The net present value after microgrid upgrade cost (10% of system capital cost) and benefits of the 2.2A system is negative in \$-32,996; while the net present value of the 2.2B

system is negative in \$-24,526 (in this case avoided outage costs ascenderían a \$8470).

Due to the fact that the photovoltaic solar panel system either has zero nominal power (Systems 2.1A and 2.1B) or has a reduced nominal power (Systems 2.2A and 2.2B), only a limited percentage of the daily energy demand can be satisfied, so it is necessary that the batteries have a large capacity (in Ah); see Table 16. In this case the battery capacity required for a 1.92 h blackout would be 19 kWh, while the capacity required for a 16 h blackout would be 89 kWh; see operating strategy in Fig. 10.

3. Scenario 3: Dimensioning of the Scheme Assuming a Hybrid System Based on Solar Energy and a Diesel Group to Meet the Needs of Electrical Resilience.

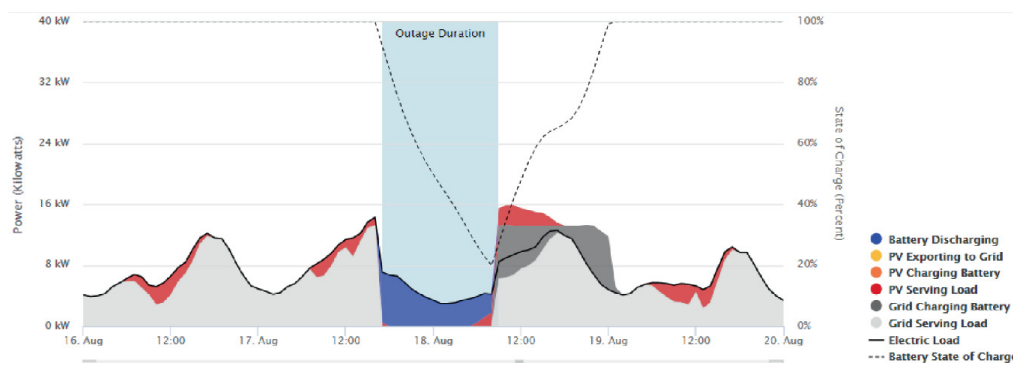


Fig. 10 Response of photovoltaic solar panels and electrochemical batteries to a 16-h blackout to satisfy critical load.

Source Adapted from ReOpt Lite software

Table 17 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 3.

Table 17 Results for 43rd Battalion scenario 3, engine 245, FDNY ladder 161

43rd Battalion, engine 245, FDNY ladder 161				
Scenario 3: dimensioning of the photovoltaic solar installation + electrochemical storage + diesel group to meet electrical resilience needs				
	System 3.1A: short blackout; no resilience value included (\$0 per kWh)	System 3.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 3.2A: long blackout; no resilience value included (\$0 per kWh)	System 3.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Size of solar photovoltaic system (kW-DC)	0	0	0	0
Electrochemical battery size (kWh)	12	12	11	11
Electrochemical battery size (kW)	2	2	5	5
Diesel Generator Size (kW)	5	5	4	4

43rd Battalion, engine 245, FDNY ladder 161				
Scenario 3: dimensioning of the photovoltaic solar installation + electrochemical storage + diesel group to meet electrical resilience needs				
	System 3.1A: short blackout; no resilience value included (\$0 per kWh)	System 3.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 3.2A: long blackout; no resilience value included (\$0 per kWh)	System 3.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Diesel generator fuel used (L)	15	15	160	160
Net present value before microgrid investment	\$-1135	\$-1135	\$-1568	\$-1568
Avoided outage costs	\$0	\$5797	\$0	\$53,811
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-2027	\$3770	\$-2452	\$51,359

Source Own elaboration

Scenario 3 demonstrates that assigning a value to resilience would result in considerable savings over Scenario 2. If assigning a value to resilience in the long duration blackout scenario (3.2B), it would result in savings to the 43rd Battalion, Engine 245, FDNY Ladder 161 of approximately \$51,359 over the 25 years of the project life cycle (relative to the current situation). For a long blackout, if no value is assigned to resilience, the 3.2A system would give the 3rd Battalion, Engine 245, FDNY Ladder 161 a net present value after microgrid upgrade cost (10% of system capital cost) of \$-2452 over the 25 years of the project life cycle. In case the 3rd Battalion, Engine 245, FDNY Ladder 161 assigns a resilience value of (\$100 per kWh) for the 25 years of the assumed life cycle, the 3.1B system would also be cost effective. Note that none of the systems recommends the use of photovoltaic solar energy (see Fig. 11, Table 17).

4. Scenario 4: Dimensioning of the Scheme Assuming a System Based Exclusively on a Diesel Group to Meet Electrical Resilience Needs.

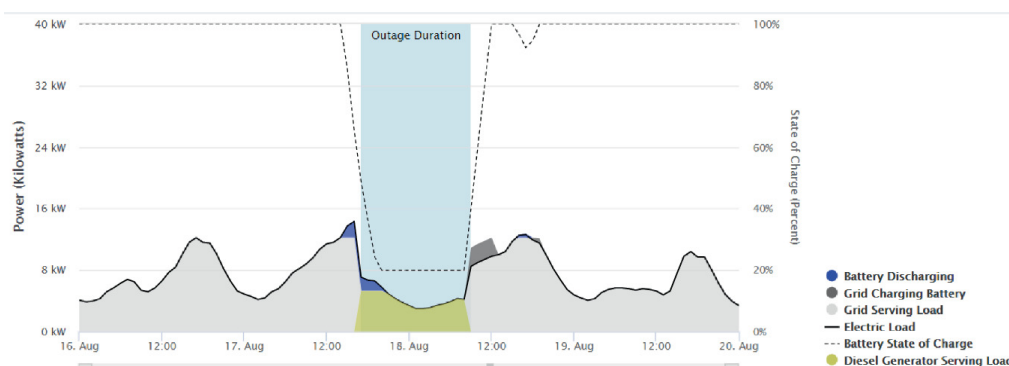


Fig. 11 Combination of use of electrochemical storage and a diesel group to cope with critical load during a 16-h blackout.

Source Adapted from ReOpt Lite software

For comparative purposes, the cost of a backup system based exclusively on a conventional diesel group has also been evaluated. Table 18 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 4.

Table 18 Results for 43rd Battalion scenario 3, engine 245, FDNY ladder 161

43rd Battalion, engine 245, FDNY ladder 161				
Scenario 4: dimensioning of the scheme assuming a system based exclusively on a diesel group to meet electrical resilience needs				
	System 4.1A: short blackout; no resilience value included (\$0 per kWh)	System 4.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 4.2A: long blackout; no resilience value included (\$0 per kWh)	System 4.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Diesel group size (kW)	7	7	7	7
Diesel generator fuel used (L)	25	25	180	180
Net present value before microgrid investment	\$-4283	\$-4283	\$-4427	\$-4427
Avoided outage costs	\$0	\$8154	\$0	\$58,357
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-4638	\$3516	\$-4782	\$53,575

Source Own elaboration

As can be seen, the size of the diesel group remains constant at 7 kW for the four systems evaluated. However, the amount of fuel increases from 25 to 180 L when the duration of the blackout increases from 1.92 to 16 h. The only system that is cost effective is the 4.2B, which assigns a value to resilience for long-lasting blackouts.

3.4 Discussion of the Results of the 43rd Battalion, Engine 245, FDNY Ladder 161 for All Scenarios

Table 19 compares the net present value for the three scenarios (2–4) that dimension the schemes based on their resilience. Table 19 shows that when assigning a specific resilience value for short-term blackouts, scenario 3 (in this specific case electrochemical storage + diesel group) has the highest net present value. If a specific resilience value is assigned for long duration blackouts, scenario 4 (diesel group) has the highest net present value.

Table 19 Comparison of net present value and simple payback for scenarios 2, 3, and 4 of the 43rd Battalion, engine 245, FDNY ladder 161

43rd Battalion, engine 245, FDNY ladder 161				
More cost-effective option for dealing with blackouts				
	Short blackout; no resilience value included (\$0 per kWh)	Short blackout; resilience is assigned a value (\$100 per kWh)	Long blackout; no resilience value included (\$0 per kWh)	Long blackout; resilience is assigned a value (\$100 per kWh)
Scenario 2: photovoltaic solar energy + electrochemical storage Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-4689	\$-3067	\$-32,996	\$-24,526
Scenario 3: photovoltaic solar energy (photovoltaic solar energy + electrochemical storage + diesel group) Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-2027	\$3770	\$-2452	\$51,359
Scenario 4: diesel group Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-4638	\$3516	\$-4782	\$53,575

Source Own elaboration

In scenario 3 (electrochemical storage + diesel group), electrochemical batteries provide demand savings during normal operation (with connection to the conventional power grid) and also to satisfy part of the critical load during blackouts. This results in a reduction in the size of the required diesel group. For all scenarios based on one diesel group only, the nominal power of the scenarios was 7 kW; for scenario 3 (electrochemical storage + diesel group) the required diesel groups had nominal powers of 5 kW. Compared to scenarios based exclusively on photovoltaic solar energy and electrochemical storage (scenario 2), systems based on electrochemical storage + diesel group (scenario 3) use a battery size with a significantly reduced capacity (19–89 versus 11–12 kWh). Dependence on diesel fuel is reduced, as expected, between Scenario 4 and Scenario 3. For Scenario 2 there is no dependence on diesel fuel.

3.5 Brighton/Manhattan Beach Senior Center

1. Scenario 1: dimensioning of the photovoltaic solar installation from an economic perspective (although no requirement is imposed regarding the resilience of the system, it is evaluated).

An overview of the dimensions and costs for Scenario 1 is presented in Table 20.

Table 20 Results for Brighton/Manhattan Beach senior center scenario 1

Brighton/Manhattan Beach senior center	
Scenario 1: scheme based on a photovoltaic solar installation and electrochemical storage from an economic perspective	
	System 1.1: no value is included for resilience
Size of solar photovoltaic system (kW-DC)	3 kW
Electrochemical battery size (kWh)	273 kWh
Electrochemical battery size (kW)	45 kW
Net present value	\$100,237

Source Own elaboration

System 1.1 is a traditional economic analysis that places no value on resilience. This scheme would save the Brighton/Manhattan Beach Senior Center \$100,237 over 25 years. These savings are obtained mainly through demand management during peak consumption periods. This fact is shown in Fig. 12, where you can see how the battery is strategically discharged to reduce peak loads.

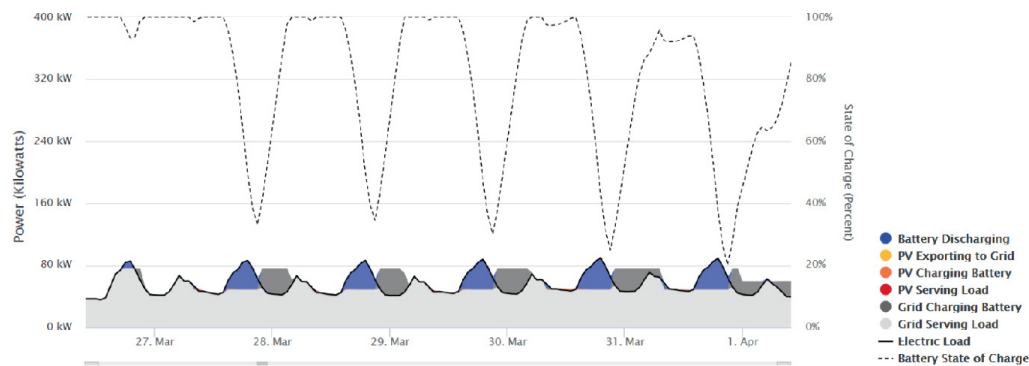


Fig. 12 Combination of use of photovoltaic solar energy and electrochemical storage to reduce peak demand.

Source Adapted from ReOpt Lite software

It then evaluated the length of time that the system based on solar photovoltaic panels and electrochemical storage was able to satisfy the critical load during a “short” blackout of 7.77 h and during a “long” blackout of 16 h. Because in this scenario the system based on photovoltaic solar panels and electrochemical storage are relatively small compared to charging, batteries are not always able to satisfy the critical load.

For the blackout that takes place in the worst case scenario (low irradiation and high electricity demand), these systems are capable of satisfying 61% of the critical load during a 7.77 h blackout (see Fig. 20). During a 16 h blackout the systems would be able to satisfy 0% of the critical load during the worst case scenario; see Table 21 and Figs. 21 and 22.

Table 21 Percentage of critical load that the system can feed

	System 1.1: no value is included for resilience (%)
7.77 h blackout (worst case)	61.1
16 h blackout (worst case)	0

	System 1.1: no value is included for resilience (%)
5 h blackout	46.85

Source Own elaboration

2. Scenario 2: Sizing of the Photovoltaic Solar Facility to Meet Electrical Resilience Needs.

Table 22 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 2.

Table 22 Results for Brighton/Manhattan Beach senior center scenario 2

Brighton/Manhattan Beach senior center				
Scenario 2: sizing of the photovoltaic solar installation + electrochemical batteries to meet electrical resilience needs				
	System 2.1A: short blackout; no resilience value included (\$0 per kWh)	System 2.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 2.2A: long blackout; no resilience value included (\$0 per kWh)	System 2.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Size of solar photovoltaic system (kW-DC)	34 kW	34 kW	105 kW	105 kW
Electrochemical battery size (kWh)	602 kWh	602 kWh	869 kWh	869 kWh
Electrochemical battery size (kW)	77 kW	77 kW	97 kW	97 kW
Net present value before microgrid investment	\$29,501	\$29,501	\$-46,331	\$-46,331
Avoided outage costs	\$0	\$66,936	\$0	\$8470
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-2759	\$64,178	\$-32,996	\$-24,526

Source Own elaboration

None of the systems in Scenario 2.2 are cost-effective. In this case systems designed to cope with longer blackouts are not able to compensate for their higher capital cost. As far as battery capacity is concerned, it is variable, requiring greater storage capacity for long term blackouts. This larger battery is required because photovoltaic solar systems are only capable of satisfying a portion of the required energy. As an example, the operating mode is shown for the critical day (August 18 at 5 pm), in which it can be seen how the battery has to provide most of the required energy (see Fig. 13).

3. Scenario 3: Dimensioning of the scheme assuming a hybrid system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience.

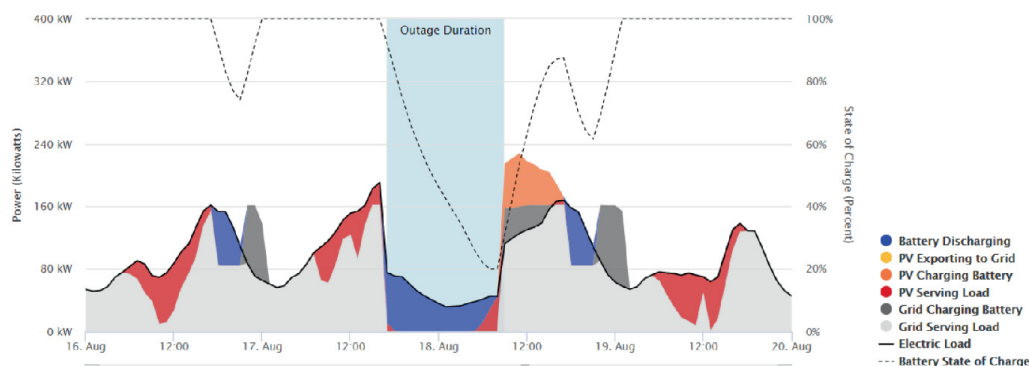


Fig. 13 Combination of use of photovoltaic solar energy and electrochemical storage to cope with critical load during a 16-h blackout.

Source Adapted from ReOpt Lite software

Table 23 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 3.

Table 23 Results for Brighton/Manhattan Beach senior center scenario 3

Brighton/Manhattan Beach senior center				
Scenario 3: dimensioning of the photovoltaic solar installation + electrochemical storage + diesel group to meet electrical resilience needs				
	System 3.1A: short blackout; no resilience value included (\$0 per kWh)	System 3.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 3.2A: long blackout; no resilience value included (\$0 per kWh)	System 3.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Size of solar photovoltaic system (kW-DC)	29	29	21	21
Electrochemical battery size (kWh)	508	508	332	332
Electrochemical battery size (kW)	70	70	53	53
Diesel generator size (kW)	14	14	36	36
Diesel generator fuel used (L)	35	35	180	180
Net present value before microgrid investment	\$54,299	\$54,299	\$74,519	\$74,519
Avoided outage costs	\$0	\$68,794	\$0	\$105,602
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$26,030	\$94,823	\$53,972	\$159,574

Source Own elaboration

All the systems assessed in Scenario 3 were cost-effective. Note how assigning a higher value to “long” resilience over “short” duration increases the net present value of the 3.2B system by about \$20,000 over the 3.2A system. The battery provides a demand saving during normal operation with mains

connection. On the other hand, and in order to reduce the size of the required diesel group and its operating time, the battery also satisfies part of the critical load during the blackout; see Fig. 14.

4. Scenario 4: Dimensioning of the Scheme Assuming a System Based Exclusively on a Diesel Group to Meet Electrical Resilience Needs.

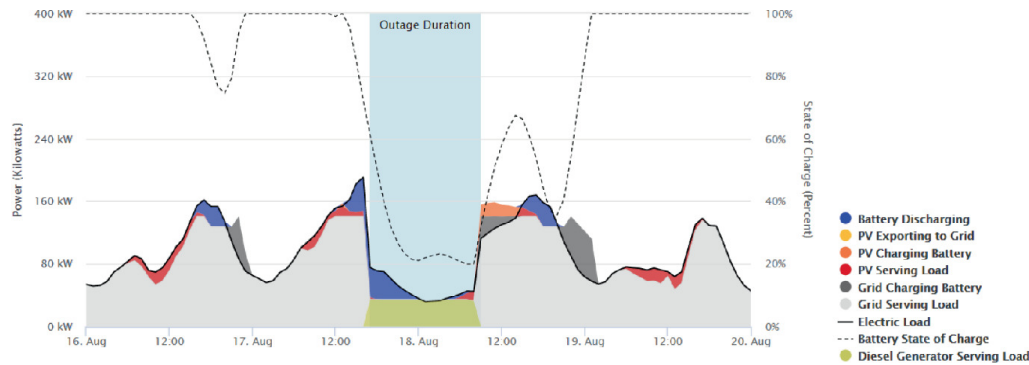


Fig. 14 Combination of use of photovoltaic solar energy, electrochemical storage and a diesel group to cope with the critical load during a 16-h blackout.

Source Adapted from ReOpt Lite software

Table 24 presents a summary of the most noteworthy aspects of the proposed scheme for Scenario 3.

Table 24 Results for Brighton/Manhattan Beach senior center scenario 4

Brighton/Manhattan Beach senior center				
Scenario 4: dimensioning of the scheme assuming a system based exclusively on a diesel group to meet electrical resilience needs				
	System 4.1A: short blackout; no resilience value included (\$0 per kWh)	System 4.1B: short blackout; resilience is assigned a value (\$100 per kWh)	System 4.2A: long blackout; no resilience value included (\$0 per kWh)	System 4.2B: long blackout; resilience is assigned a value (\$100 per kWh)
Diesel group size (kW)	76	76	76	76
Diesel generator fuel used (L)	130	130	225	225
Net present value before microgrid investment	\$-46,152	\$-46,152	\$-46,826	\$-46,826
Avoided outage costs	\$0	\$45,940	\$0	\$78,776
Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-49,929	\$-3989	\$-50,603	\$28,143

Source Own elaboration

For comparative purposes the cost of an emergency system was also evaluated in a system based exclusively on a diesel generator. A diesel generator is only cost effective in Scenario 4.2 for a long blackout when a value is assigned to resilience. The rated power of the diesel generator remains unchanged for all four scenarios at 76 kW. However, the amount of fuel required increases from 130 to 225 L).

3.6 Discussion of Brighton/Manhattan Beach Senior Center Results for All Scenarios

Table 25 compares the net present value for the three scenarios (2–4) that dimension the schemes based mainly on their resilience. Table 25 shows that scenario 3 (photovoltaic solar energy + electrochemical storage + diesel group) represents the best option from the point of view of the economic feasibility of the system to satisfy short and long term blackouts.

Table 25 Comparison of net present value and simple payback for scenarios 2, 3, and 4 of the Brighton/Manhattan Beach senior center

Brighton/Manhattan Beach senior center				
More cost-effective option for dealing with blackouts				
	Short blackout; no resilience value included (\$0 per kWh)	Short blackout; resilience is assigned a value (\$100 per kWh)	Long blackout; no resilience value included (\$0 per kWh)	Long blackout; resilience is assigned a value (\$100 per kWh)
Scenario 2: photovoltaic solar energy + electrochemical storage Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-2759	\$64,178	\$-32,996	\$-24,526
Scenario 3: photovoltaic solar energy (photovoltaic solar energy + electrochemical storage + diesel group) Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$26,030	\$94,823	\$53,972	\$159,574
Scenario 4: diesel group Net present value after microgrid upgrade cost (10% of system capital cost) and benefits	\$-49,929	\$-3989	\$-50,603	\$28,143

Source Own elaboration

For all the cases studied the way in which the resilience value is evaluated will influence the type of emergency system that the site will have to install. Regardless of whether or not these sites assign an economic value to resilience, if you want to have a system that addresses the possible blackouts that may occur throughout the year, the recommendation would be to install a hybrid

system based on photovoltaic solar energy and a diesel group to meet the needs of electrical resilience. If emergency power is seen as a secondary benefit to the economic benefits a resilient system can provide, Scenario 1 is recommended. Scenario 1 systems will allow the site to obtain a return on investment while receiving, depending on when the blackout occurs, a limited amount of emergency power.

4 Conclusions

The research presented here modeled resilient systems based on solar photovoltaic energy specifically designed to obtain economic savings and examined the amount of backup energy they are able to provide. The analysis also modeled systems based on a combination of photovoltaic solar energy, electrochemical batteries and diesel groups designed to meet emergency energy needs, which could also be used to obtain economic savings during normal operation connected to the conventional electricity grid. Finally, in order to compare traditional solutions for improving resilience with other solutions based on renewable energies, the analysis also evaluated systems based exclusively on diesel generators designed to meet emergency power needs.

The results for the three sites indicate that systems based on Photovoltaic Solar Energy + Electrochemical Storage; and systems based on Photovoltaic Solar Energy + Electrochemical Storage + Diesel Group, can provide a positive net present value whether or not they are assigned a resilience value. Regarding the economic viability of resilient systems based on photovoltaic solar energy is, in general, higher than that of “classic” solar photovoltaic installations, mainly due to the ability of batteries to reduce the energy demand.

It should be noted that, when a value is assigned to resilience, the economic viability of projects for all modeled systems is greatly improved for radio network customers. This is due to the higher frequency of blackouts on radial networks compared to meshed networks. When a value is assigned to resilience, the economic viability for all systems modelled in meshed networks is moderately improved.

It should also be noted that those systems based on photovoltaic solar energy specifically designed to obtain economic savings (not to obtain an improvement in resilience) are capable of providing limited benefits in terms of resilience. In this sense, the level of resilience provided by resilient systems based on photovoltaic solar energy + electrochemical storage will depend on when the blackout occurs, the state of charge of the battery and the size of the charge.

Finally, it should be noted that resilient systems based on photovoltaic solar energy + electrochemical storage; and resilient systems based on photovoltaic solar energy + electrochemical storage + diesel group that have been designed to cope with short and long term blackouts, result in larger and more expensive systems than systems designed exclusively to obtain economic savings. In some cases, assigning a value to the possibility of avoiding electricity blackouts may offset the additional costs incurred in sizing systems from a resilient perspective rather than taking into account purely economic criteria. Diesel groups as a resilient solution do not have a positive net present value except

when resilience is assigned a value in “long” blackouts. Although diesel generators are the most commonly used emergency technology, systems based on Photovoltaic Solar Energy + Electrochemical Storage; and systems based on Photovoltaic Solar Energy + Electrochemical Storage + Diesel Group can offer the same benefits at a lower cost throughout the life cycle of the project. In global lines, the results of the research presented here show that systems based on photovoltaic solar energy + electrochemical storage (and with diesel generators in case resilience is a priority), can be advantageous from an economic point of view depending on the recovery requirements of the investment made.

Appendix 1: Assumptions for the Analysis

Input	Suggested value	Range of values	Source
<i>Location and electricity distributor</i>			
Site location	New York, NY	/	
Electricity rate Tottenville high school	SC-9—general large low tension service (NYC)	/	[53]
Electricity rate 3rd Battalion, engine 245, FDNY ladder 161	SC-9—general large low tension service (NYC)	/	[53]
Electricity rate Brighton/Manhattan Beach senior center	SC 8—multiple dwellings redistribution TOD service (NYC)	/	[63]
Net metering	0 (it will be assumed that the installation is not subject to the Net Balance)	It depends on the legislation in each country	[81]
Wholesale rate (\$/kWh)	0	Typically 0-0.05 (highly variable)	[82]
Site name 1 (Tottenville high school)	High school	/	[47]
Site name 2 (3rd Battalion, engine 245, FDNY ladder 161)	Fire station	/	[55]
Site name 3 (Brighton/Manhattan Beach senior center)	Senior Center	/	[59]
Land available Tottenville high school (acres/m ²)	0.65 acres (2632 m ²)	/	
Land available 3rd Battalion, engine 245, FDNY ladder 161 (acres/m ²)	0.12 acres (485 m ²)	/	
Land available Brighton/Manhattan Beach senior center (acres/m ²)	0.41 acres (1650 m ²)	/	

Input	Suggested value	Range of values	Source
Roofspace available (Tottenville high school)	0.65 acres (2632 m ²)	/	
Roofspace available (3rd Battalion, engine 245, FDNY ladder 161)	0.12 acres (485 m ²)	/	
Roofspace available (Brighton/Manhattan Beach senior center)	0.41 acres (1650 m ²)	/	
<i>Load profile</i>			
Type of building (Tottenville high school)	School—secondary	/	
Type of building (3rd Battalion, engine 245, FDNY ladder 161)	Midrise apartment	/	
Type of building (Brighton/Manhattan Beach senior center)	Midrise apartment	/	
Annual energy consumption (Tottenville high school)	1,883,392 kWh/year	/	Data provided by the U.S. Department of Energy and the New York City Climate Zone (ASHRAE Climate Zone 4A) included in REopt software
Annual energy consumption (43rd Battalion, engine 245, FDNY ladder 161)	42,530 kWh/year	/	Data provided by the U.S. Department of Energy and the New York City Climate Zone (ASHRAE Climate Zone 4A) included in REopt software
Annual energy consumption (Brighton/Manhattan Beach senior center)	564,896 kWh/year	/	Data provided by the U.S. Department of Energy and the New York City Climate Zone (ASHRAE Climate Zone 4A) included in REopt software
Critical load factor (%) (Tottenville high school)	10%	The critical load factor varies greatly depending on the ultimate purpose of the building	[54]
Critical load factor (%) (3rd Battalion, engine 245, FDNY ladder 161)	50%	The critical load factor varies greatly depending on the ultimate purpose of the building	[57, 58]
Critical load factor (%) (Brighton/Manhattan Beach senior center)	40%	The critical load factor varies greatly depending on the ultimate purpose of the building	[57]
<i>Financial</i>			
Host discount rate, nominal (%)	8.1%	2.4–15%	[83, 84]

Input	Suggested value	Range of values	Source
Electricity cost escalation rate, nominal (%)	2.6%	−0.5 and 5.5%	[84–86]
Analysis period (years)	20	10–40	[83, 87]
Host effective tax rate (%)	26%		[83–89]
O&M cost escalation rate (%)	2.5%	−0.6 and 4%	[83, 84, 90]
<i>Resilience</i>			
Outage duration (h) (Tottenville high school)	7.77 (short), 16 (long)	0–71 h	[77]
Outage duration (h) (3rd Battalion, engine 245, FDNY ladder 161)	1.92 (short), 16 (long)	0–71 h	[77]
Outage duration (h) (Brighton/Manhattan Beach senior center)	7.77 (short), 16 (long)	0–71 h	[77]
Outage start date (Tottenville high school)	June 30		Reopt autoselect outage start date option
Outage start date (3rd Battalion, Engine 245, FDNY ladder 161)	August 17		Reopt autoselect outage start date option
Outage start date (Brighton/Manhattan Beach senior center)	August 17		Reopt autoselect outage start date option
Outage start time (Tottenville high school)	3 pm		Reopt autoselect outage start date option
Outage start time (3rd Battalion, engine 245, FDNY ladder 161)	5 pm		Reopt autoselect outage start date option
Outage start time (Brighton/Manhattan Beach senior center)	3 pm		Reopt autoselect outage start date option
Type of outage event	Major outage—Occurs once per Project lifetime	/	/
Fuel burn rate for diesel generator	0.078 gal/kWh 0.2952 l/kWh		[91]
Fuel curve and intercept by generator capacity	0.009 gal/h 0.034 l/h	0.004–0.0142 gal/h 0.01514165–0.05375285 l/h	[92–95]
Minimum loading for diesel generator (% of capacity)	30%		[96–98]
Microgrid upgrade cost (% of system capital cost)	30%	/	
Avoided outage costs (\$/kWh)	100 \$/kWh	0.0032–432.89 \$/kWh	[99–101]
<i>Photovoltaic system</i>			
System capital cost (\$/kW)	\$2000	\$1638–2180	[83, 102]
Capital cost based incentives	30% Federal (the rest with the default values)		[103–105]

Input	Suggested value	Range of values	Source
	ITC, 5 year MACRS		
O&M cost (\$/kW/year)	\$16	\$11-20	[83]
Minimum size desired (kW DC)	0 kW	/	
Maximum size desired (kW DC)	Unlimited	/	
Module type	Standard	/	
Array azimuth	180° (we are going to assume that they are perfectly oriented towards the South) ///////// 0° North 90° East 180° South 270° West	0-360°	[106]
Array tilt—rooftop, fixed ²	10°	0-60°	[107]
DC to AC ratio ³	1.10	1.10-1.50	[108, 109]
System losses—soiling	2%	2-25%	[108-110]
System losses—shading	3%	0-30%	[108-111]
System losses—snow	0%	Although from 0 to 15% is usual, it can be up to 100%	[108-110, 112]
System losses—mismatch ⁴	2%	1.5-3%	[108-110]
System losses—wiring	2%	0.7-2%	[108-110]
System losses—connection	0.5%	0.3-0.1%	[108-110]
System losses—light-induced degradation (LID) ⁵	1.5%	0.3-10%	[108-110]
System losses—age	3%	0-100%	[108, 109]
Total system losses = system losses due to dirt + System losses due to shadows + System losses due to snow + Losses of the system due to Mismatching or coupling effect + Losses in drivers + Losses in diodes and connections + Losses due to light-induced degradation (LID) + Losses due to aging	14%	5-100%	
MACRS ⁶ schedule	5 years	5-7 years	[113]
Storage (note that all values listed assume the use of ion lithium batteries)			

Input	Suggested value	Range of values	Source
Energy capacity cost (\$/kWh)	\$500	\$400-690	[114-117]
Power capacity cost (\$/kW) ⁷	\$1000	\$800-1375	[114-117]
Battery energy capacity replacement cost (\$/kWh)	\$230	\$170-300	[114, 115]
Energy capacity replacement year	10	Although 4-20 years is possible, it is likely that this amount will vary between 8 and 15 years	[118-122]
Power capacity replacement cost (\$/kW)	\$460	\$350-550	[118-122]
Power capacity replacement year	10	10-15	[118-122]
Rectifier efficiency (%) ⁸	96%		[123]
Round trip efficiency (%)	97.5%	95-98%	[119, 123]
Inverter efficiency (%)	96		[123]
Minimum state of charge (%) ⁹	20	15-30%	[123]
Minimum state of charge (%)	50		
Allow grid to charge battery	Yes		
Incentives	0% ITC		[103-105]
Total rebate (\$/kW)	0		
MACRS ¹⁰ schedule	7 years	5-7 years	[124-140]

Appendix 2: System Performance Year One for a Number of Systems

See Figs. 15, 16, 17, 18, 19, 20, 21, and 22.

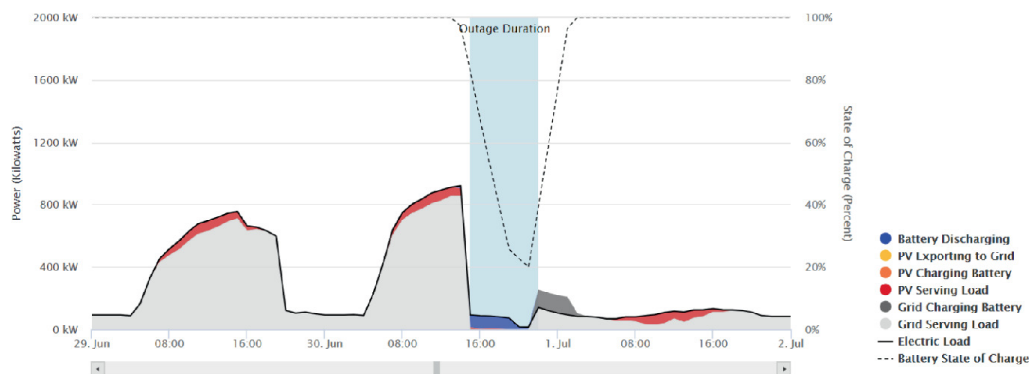


Fig. 15 System performance year one for system 1.2 (Tottenville High School).

Source Adapted from ReOpt Lite software

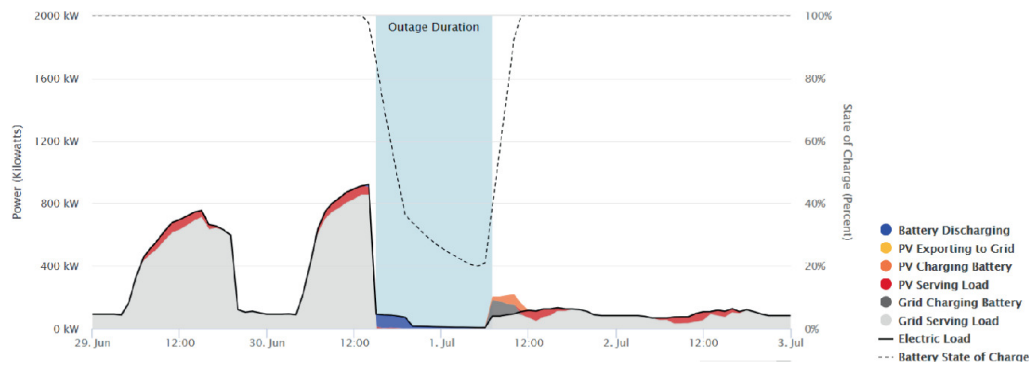


Fig. 16 System performance year one for system 1.3 (Tottenville High School).
Source Adapted from ReOpt Lite software

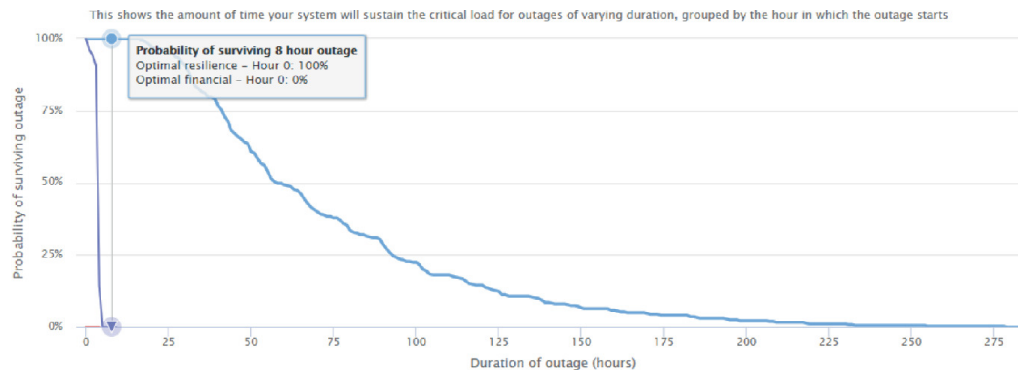


Fig. 17 Amount of time the system 1.2 will sustain the critical load for "short" outages for the worst case (Tottenville High School).
Source Adapted from ReOpt Lite software

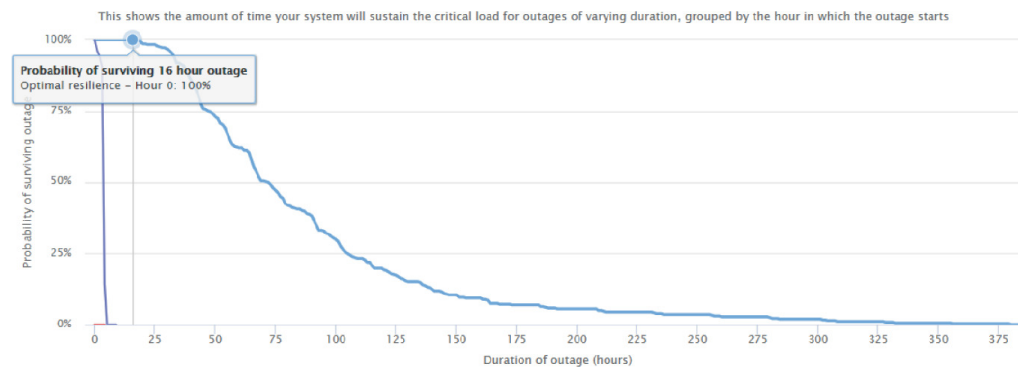


Fig. 18 Amount of time the system 1.3 will sustain the critical load for "long" outages for the worst case (Tottenville High School).
Source Adapted from ReOpt Lite software

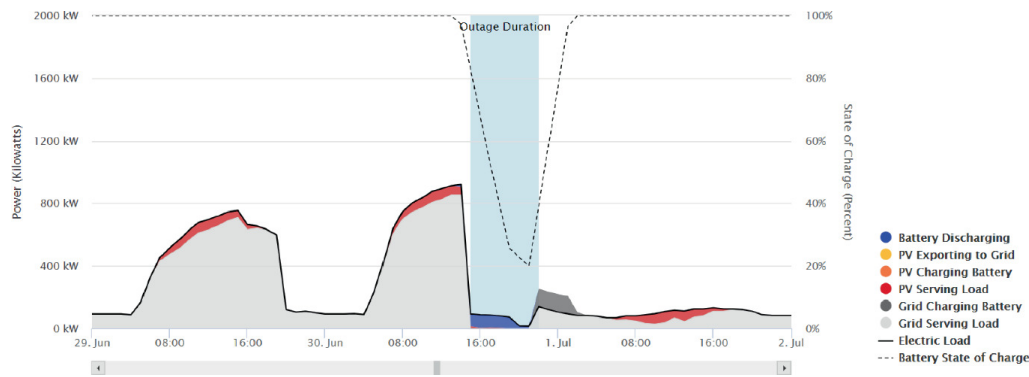


Fig. 19 System performance year one for system 3.1B (Tottenville High School).
Source Adapted from ReOpt Lite software

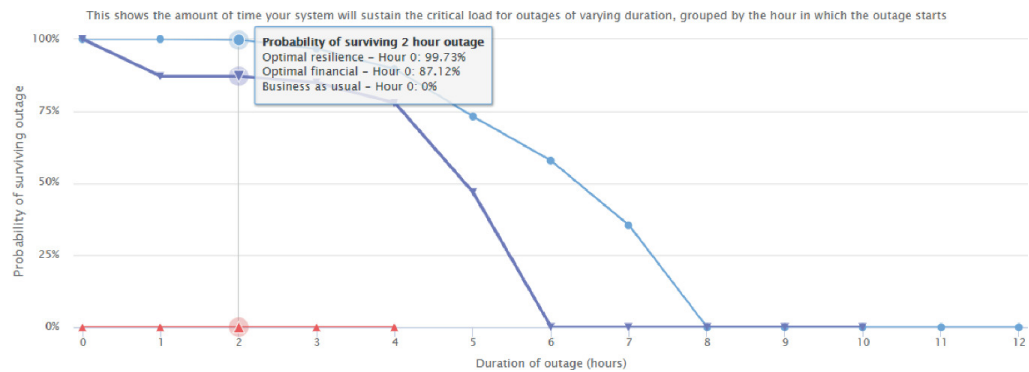


Fig. 20 Amount of time that your system can survive grid outages for system 1.1 (43rd Battalion, Engine 245, FDNY Ladder 161).
Source Adapted from ReOpt Lite software

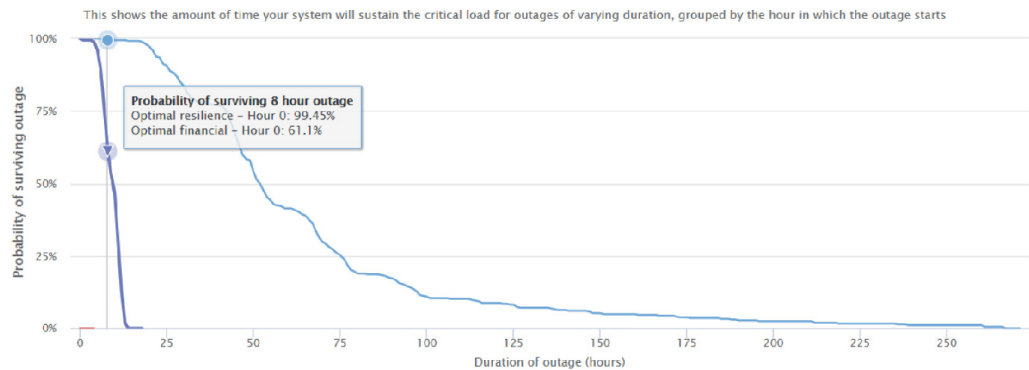


Fig. 21 Amount of time that your system can survive grid outages for system 1.1 for the "short" outage (Brighton/Manhattan Beach Senior Center).
Source Adapted from ReOpt Lite software

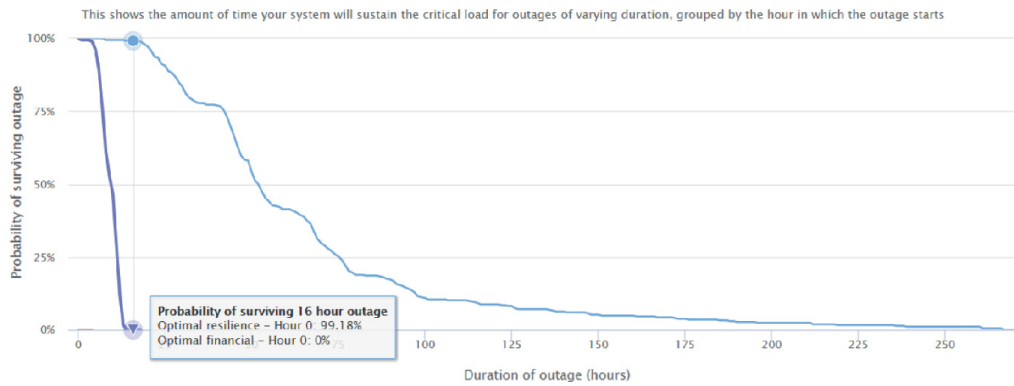


Fig. 22 Amount of time that your system can survive grid outages for system 1.1 for the “long” outage (Brighton/Manhattan Beach Senior Center).

Source Adapted from ReOpt Lite software

References

1. Alsayyed N (2016) Regulatory islanding parameters in battery based solar PV for electricity system resiliency. *IEEE Trans Sustain Energy* 6(2):30–41
2. NREL (2014) Distributed solar PV for electricity system resiliency: policy and regulatory considerations. <https://www.nrel.gov/docs/fy15osti/62631.pdf>. Accessed 26 June 2019
3. The World Bank (2017) Energy resilience takes on renewed urgency. <https://www.worldbank.org/en/news/feature/2017/11/10/energy-resilience-takes-on-renewed-urgency>. Accessed 26 June 2019
4. U.D. Department of Energy (2018) Strengthening the security and resilience of the nation’s critical energy infrastructure. <https://www.energy.gov/oe/articles/strengthening-security-and-resilience-nation-s-critical-energy-infrastructure>. Accessed 26 June 2019
5. Zhao L, Li H, Sun Y, Huang R, Hu Q, Wang J et al (2017) Planning emergency shelters for urban disaster resilience: an integrated location-allocation modeling approach. *Sustainability* 9(11):1–20
6. Diesel Service and Supply (2019) Emergency standby power: protecting the nation's power grid with diesel generators. https://www.dieselserviceandsupply.com/Emergency_vs_Prime.aspx. Accessed 26 June 2019
7. Maryland Energy Administration (2015) Resiliency through microgrids: task force report. https://energy.maryland.gov/Documents/MarylandResiliencyThroughMicrogridsTaskForceReport_000.pdf. Accessed 26 June 2019
8. Kostro SS, Riba G (2014) Achieving disaster resilience in U.S. Communities: executive branch, congressional, and private-sector efforts. Rowman & Littlefield Publishers/Center for Strategic & International Studies, Lanham
9. Rentschler J, Kornejew M, Hallegatte S, Braese J, Obolensky M (2019) Underutilized potential: the business costs of unreliable infrastructure in developing countries. World Bank Group, Washington
10. Gundlach J (2018) Microgrids and resilience to climate-driven impacts on public health. Columbia Law School, Sabin Center for Climate Change Law
11. New York State Energy Research and Development Authority (2016) NY prize task 5 milestone deliverable: village of Tarrytown, final report. <https://www.nyserda.ny.gov/-/media/NYPrize/files/studies/25-Village-of-Tarrytown.pdf>. Accessed 27 June 2019
12. Ribeiro D, Mackres E, Baatz B, Cluett R, Jarrett M, Kelly M et al (2015) Enhancing community resilience through energy efficiency. American Council for an Energy-Efficient Economy, Washington
13. Gibbs LI, Holloway CF (2013) Hurricane Sandy after action: report and recommendations to Mayor Michael R. Bloomberg. City of New York, New York

14. New York City Fire Department (2015) Study material for the certificate of fitness examination for use of flammable gases with oxygen or use of LPG/CNG for hot work operations (citywide) G-60. New York City Fire Department, New York
15. Central Maine Diesel (2019) Perkins 175,000 Watt 6.6 L in-line 6 cylinder Perkins Diesel. <http://www.centralmainediesel.com/order/Perkins-175-kw-diesel-generator.asp?page=Perkins175>. Accessed 27 June 2019
16. Office of Utilities Regulation (2020) Jamaica public service company limited tariff review for period 2014–2019: determination notice. http://www.our.org.jm/ourweb/sites/default/files/C-JPS%20Tariff%20Review%20for%20Period%202014-2019_Determination%20Notice.compressed.pdf. Accessed 26 June 2019
17. State of New York Public Service Commission (2019) CASE 09-E-0428—proceeding on motion of the commission as to the rates, charges, rules and regulations of consolidated Edison company of New York, Inc. for electric service. <http://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7BF4797A12-4B20-4AF8-B3E6-AFC3D76E0DCB%7D>. Accessed 26 June 2019
18. Electric Distribution Systems: Office of Electric, Gas, and Water (2016) Electric reliability performance report. <http://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7BBBCBF3C3-1812-4EEC-9E31-6901AED885D3%7D>. Accessed 26 June 2019
19. New York City Economic Development Corporation (2020) Liquid fuels. https://www.nycedc.com/sites/default/files/filemanager/Resources/Studies/Stronger_More_Resilient_NY/Ch7_Liquid_Fuels_FINALsingles.pdf. Accessed 26 June 2019
20. US Department of Homeland Security (2022) FEMA has no assurance that only designated recipients received \$6.37 million in fuel. <https://www.oig.dhs.gov/sites/default/files/assets/GrantReports/2016/OIG-16-04-D-Nov15.pdf>. Accessed 26 June 2019
21. Anderson K, Laws ND, Marr S, Lisell L, Jimenez Y, Case T et al (2018) Quantifying and monetizing renewable energy resiliency. *Sustainability* 10(4):1–13
22. US Executive Office of the President (2013) Economic benefits of increasing electric grid resilience to weather outages. The White House, Washington
23. PowerStar (2020) UPS expertise. <http://powerstarups.com/upszhishi/2025.html?lang=en>. Accessed 28 June 2019
24. Obolensky M, Erman A, Rozenberg J, Rentschler J, Avner P, Hallegatte S (2019) Infrastructure disruptions how instability breeds household vulnerability. World Bank Group, Washington
25. Office of Governor Martin O'Malley (2020) Weathering the storm: report of the grid resiliency task force. https://www.bateswhite.com/media/publication/13_GridResiliencyTaskForceReport.pdf. Accessed 28 June 2019
26. Sustainable CUNY (2020) Resilient solar photovoltaics (PV) systems. <https://nysolarmap.com/media/1451/dechardwarefactsheet.pdf>. Accessed 01 July 2019
27. CleanEnergyGroup (2016) The economics of resilient solar+storage for critical infrastructure. <https://www.cleanegroup.org/wp-content/uploads/Webinar-Slides-9.14.16.pdf>. Accessed 01 July 2019
28. Sustainable CUNY of the City University of New York (2018) Smart DG hub storage 101. https://cadmusgroup.com/wp-content/uploads/2018/03/Cadmus-Smart-DG-HUB_-Storage-101.pdf. Accessed 01 July 2019
29. Perez R, Rábago KR, Trahan M, Rawlings L, Norris B, Hoff T et al (2006) Achieving very high PV penetration: the need for an effective electricity remuneration framework and a central role for grid operators. *Energy Policy* 96:27–35
30. NYStatesolar (2013) New York increased its Solar Power use almost 800%. <https://nystatesolar.com/author/alexramogmail-com/>. Accessed 02 July 2019
31. New York State. Building a clean, resilient, and affordable energy system for all New Yorkers. <https://energyplan.ny.gov/>. Accessed 02 July 2019

32. Solar Energy Industries Association. New York Solar. <https://www.seia.org/state-solar-policy/new-york-solar>. Accessed 02 July 2019
33. Local Energy Scotland. Energy systems toolkit: electrical energy storage module. <https://www.localenergy.scot/media/107014/hie-electrical-energy-storage-module.pdf>. Accessed 02 July 2019
34. Sussman M, Lutton J (2021) The economics of solar, storage and solar-plus-storage: Woodlawn Associates (with some help from Geli) examines when solar, storage or solar-plus-storage makes sense. <https://www.greentechmedia.com/articles/read/the-economics-of-solar-storage-and-solar-plus-storage#gs.mcxn7o>. Accessed 02 July 2019
35. ENELX. FAQ: New York's energy storage and solar-plus-storage opportunities. https://www.enelx.com/content/dam/enel-x-na/resources/data-sheets-and-brochures/P19036_FAQ_NY_Solar_Storage.pdf. Accessed 02 July 2019
36. Panwar M, Chanda S, Mohanpurkar M, Luo Y, Dias F, Hovsopian R, Srivastava AK (2019) Integration of flow battery for resilience enhancement of advanced distribution grids. *Int J Electr Power Energy Syst* 109:314–324
37. Mohagheghi S, Rebennack S (2015) Optimal resilient power grid operation during the course of a progressing wildfire. *Int J Electr Power Energy Syst* 73:843–852
38. Shahid MU, Khan MM, Hashmi K, Boudina R, Khan A, Yuning J et al (2019) Renewable energy source (RES) based islanded DC microgrid with enhanced resilient control. *Int J Electr Power Energy Syst* 113:461–471
39. Rocchetta R, Patelli E (2018) Assessment of power grid vulnerabilities accounting for stochastic loads and model imprecision. *Int J Electr Power Energy Syst* 98:219–232
40. Barnes A, Nagarajan H, Yamangil E, Bent R, Backhaus S (2019) Resilient design of large-scale distribution feeders with networked microgrids. *Electr Power Syst Res* 171:150–157
41. Ilo A (2016) “Link”—the smart grid paradigm for a secure decentralized operation architecture. *Electr Power Syst Res* 131:116–125
42. Khomami MS, Sepasian MS (2018) Pre-hurricane optimal placement model of repair teams to improve distribution network resilience. *Electr Power Syst Res* 165:1–8
43. Hussain A, Bui VH, Kim HM (2019) Microgrids as a resilience resource and strategies used by microgrids for enhancing resilience. *Appl Energy* 240:56–72
44. Ding T, Lin Y, Bie Z, Chen C (2017) A resilient microgrid formation strategy for load restoration considering master-slave distributed generators and topology reconfiguration. *Appl Energy* 199:205–216
45. Lin Y, Bie Z (2018) Tri-level optimal hardening plan for a resilient distribution system considering reconfiguration and DG islanding. *Appl Energy* 210:1266–1279
46. Mousavizadeh S, Haghifam MR, Shariatkhah MH (2018) A linear two-stage method for resiliency analysis in distribution systems considering renewable energy and demand response resources. *Appl Energy* 211:443–460
47. Tottenville High School. <https://sites.google.com/tottenvillehs.com/tottenvillehscommunity/home>. Accessed 21 Oct 2019
48. The observer. Aftermath of destruction from Hurricane Sandy in Staten Island. <https://fordhamobserver.com/13321/multimedia/aftermath-of-destruction-from-hurricane-sandy-in-staten-island/>. Accessed 21 Oct 2019
49. Politico. Staten Islanders tell of heart-stopping rescues, heartbreaking losses as death toll mounts. <https://www.politico.com/states/new-york/albany/story/2012/11/staten-islanders-tell-of-heart-stopping-rescues-heartbreaking-losses-as-death-toll-mounts-067223>. Accessed 21 Oct 2019
50. MILB. Hurricane Sandy Relief Resources. <https://www.milb.com/staten-island/news/hurricane-sandy-relief-resources/c-40286068>. Accessed 21 Oct 2019

51. Macaulay Honors College. Manitta, rebuilding and preventing: effects of hurricane sandy on Staten Island. <https://eportfolios.macaulay.cuny.edu/karacas2017/2017/05/26/manitta-rebuilding-and-preventing-effects-of-hurricane-sandy-on-staten-island/?highlightmarker=27>. Accessed 21 Oct 2019
52. New York Public Radio. Sharing school space starts without incident. <https://www.wnyc.org/story/302959-sharing-school-space-starts-without-incident/>. Accessed 21 Oct 2019
53. OpenEI. SC-9: general large low tension service [NYC]. <https://openei.org/apps/USURDB/rate/view/5cd1f9905457a3b21b54e9d5>. Accessed 26 Oct 2019
54. Clean Coalition. The community microgrid initiative: the path to resilience and sustainability. https://clean-coalition.org/wp-content/uploads/2018/11/CMI-presentation-Aug-2018-mr_03-29-Aug-2018.pdf. Accessed 26 Oct 2019
55. FDNY. FDNY firehouse listing. <https://data.cityofnewyork.us/api/views/hc8x-tcnd/rows.pdf?accessType=DOWNLOAD>. Accessed 21 Oct 2019
56. Department of Homeland Security. Facility-Specific descriptions of critical facilities and key assets. https://www.fema.gov/media-library-data/1385590865538-0c10ec4ba66e38db446a93689445ba9e/Sandy_MAT_AppH_508post.pdf. Accessed 21 Oct 2019
57. Paul Guyer J. Introduction to electrical power requirements for buildings. <https://www.cedengineering.com/userfiles/Intro%20to%20Electric%20Power%20Requirements.pdf>. Accessed 29 Oct 2019
58. Department of Energy. Solar market pathways: critical load document. http://solarmarketpathways.org/wp-content/uploads/2017/08/sfe_ee_sp_assessing_critical_loads_5_bldg_types.pdf. Accessed 29 Oct 2019
59. Senior Center. Jasa: Brighton/Manhattan Beach senior center—senior center in Brooklyn NY. https://seniorcenter.us/sc/jasa_brighton_manhattan_beach_senior_center_brooklyn_ny. Accessed 22 Oct 2019
60. TABLETMAG. At a Jewish senior center in Brooklyn, anxiety looms a year after Hurricane Sandy. <https://www.tabletmag.com/jewish-news-and-politics/150020/sandy-a-year-later>. Accessed 22 Oct 2019
61. New York State. Brighton beach, Coney Island, Manhattan Beach, and Sea Gate NY rising community reconstruction plan. https://stormrecovery.ny.gov/sites/default/files/crp/community/documents/brightonbeach-coneyisland-manhattanbeach-sea_gate_nyr-cr-plan.pdf. Accessed 29 Oct 2019
62. Boro Park. Battle is on to save senior centers. <http://www.boroparky.org/index.php?src=newsubmenu=Homerctype=detailcategory=Senior%20Center%20in%20the%20Newsefno=7>. Accessed 29 Oct 2019
63. OpenEI. SC 8: multiple dwellings redistribution TOD service [NYC]. <https://openei.org/apps/IURDB/rate/view/5cd1f2ce5457a3a52a54e9d7>. Accessed 29 Oct 2019
64. IEEE. IEEE recommended practice for interconnecting distributed resources with electric power systems distribution secondary networks. <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6022734>. Accessed 29 Oct 2019
65. NREL. REopt lite. <https://reopt.nrel.gov/tool>. Accessed 29 Oct 2019
66. NREL. REopt lite web tool user manual. <https://reopt.nrel.gov/tool/REopt%20Lite%20Web%20Tool%20User%20Manual.pdf>. Accessed 29 Oct 2019
67. Cutler D, Olis D, Elggqvist E, Li X, Laws N, DiOrio N, et al (2017) REopt: a platform for energy system integration and optimization. National Renewable Energy Laboratory, Golden
68. LaCommare KH, Eto JH (2004) Understanding the cost of power interruptions to U.S. electricity consumers. Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley
69. Sullivan MJ, Mercurio M, Schellenberg J, Freeman MA (2009) Estimated value of service reliability for electric utility customers in the United States. Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley

70. Bernal-Agustín L, Dufo-López R (2006) Economical and environmental analysis of grid connected photovoltaic systems in Spain. *Renew Energy* 31(8):1107–1128
71. Anderson K, Laws ND, Marr S, Lisell L, Jimenez T, Case T et al (2018) Quantifying and monetizing renewable energy resiliency. *Sustainability* 10(4):933
72. LaCommare KH, Eto JH (2006) Cost of power interruptions to electricity consumers in the United States (U.S.). Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley
73. National Infrastructure Advisory Council (2018) Surviving a catastrophic power outage: how to strengthen the capabilities of the Nation. National Infrastructure Advisory Council, Washington
74. Giraldez J, Booth S, Anderson K, Massey K (2012) Valuing energy security: customer damage function methodology and case studies at DoD installations. National Renewable Energy Laboratory, Golden. <https://www.osti.gov/servlets/purl/1055367>. Accessed 4 Nov 2019
75. Department of Energy. Interruption cost estimate (ICE) calculator. <https://icecalculator.com/home>. Accessed 4 Nov 2019
76. Larsen PH, Boehlert B, Eto JH, Hamachi-LaCommare K, Martinich J, Rennels L (2017) Projecting future costs to U.S. electric utility customers from power interruptions. Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley. https://www.ourenergypolicy.org/wp-content/uploads/2017/02/lbnl-1007027_1.pdf. Accessed 4 Nov 2019
77. Electric Distribution Systems (2018) Office of electric, gas, and water. In: Proceedings of the 2018 electric reliability performance report. New York State, Department of Public Service, New York. [http://www3.dps.ny.gov/W/PSCWeb.nsf/96f0fec0b45a3c6485257688006a701a/d82a200687d96d3985257687006f39ca/\\$FILE/Electric%20Reliability%202018%20DMM.pdf](http://www3.dps.ny.gov/W/PSCWeb.nsf/96f0fec0b45a3c6485257688006a701a/d82a200687d96d3985257687006f39ca/$FILE/Electric%20Reliability%202018%20DMM.pdf). Accessed 4 Nov 2019
78. Electric Distribution Systems (2015) Office of electric, gas, and water. In: Proceedings of the 2015 electric reliability performance report. New York State, Department of Public Service, New York. [http://www3.dps.ny.gov/W/PSCWeb.nsf/96f0fec0b45a3c6485257688006a701a/d82a200687d96d3985257687006f39ca/\\$FILE/93222265.pdf/2015%20Electric%20Reliability%20Report.pdf](http://www3.dps.ny.gov/W/PSCWeb.nsf/96f0fec0b45a3c6485257688006a701a/d82a200687d96d3985257687006f39ca/$FILE/93222265.pdf/2015%20Electric%20Reliability%20Report.pdf)
79. Bindner H, Cronin T, Lundsager P, Manwell JF, Abdulwahid U, Baring-Gould I (2005) Lifetime modelling of lead acid batteries. Risø National Laboratory, Roskilde
80. International Telecommunication Union (2018) Series 1: environment and ICTS, climate change, e-waste, energy efficiency; construction, installation and protection of cables and other elements of outside plant Innovative energy storage technology for stationary use—part 2: battery. International Telecommunication Union, Geneva. https://www.itu.int/rec/dologin_pub.asp?lang=s&id=T-REC-L.1221-201811-I!!PDF-E&type=items. Accessed 7 Nov 2019
81. DSIRE. Net Metering. N.C. Clean Energy Technology Center, Raleigh. <https://programs.dsireusa.org/system/program/detail/453>. Accessed 14 Nov 2019
82. U.S. Energy Information Administration. Rising solar generation in California coincides with negative wholesale electricity prices. U.S. Energy Information Administration, Washington. <https://www.eia.gov/todayinenergy/detail.php?id=30692#tab1>. Accessed 14 Nov 2019
83. NREL. Annual technology baseline: electricity. NREL, Denver. <https://atb.nrel.gov/>. Accessed 14 Nov 2019
84. NIST. Energy price indices and discount factors for life-cycle cost analysis—2018 annual supplement to NIST handbook 135. NIST, Gaithersburg. <https://nvlpubs.nist.gov/nistpubs/ir/2018/NIST.IR.85-3273-33.pdf>. Accessed 14 Nov 2019
85. U.S. Energy Information Administration. Energy prices: residential—propane. U.S. Energy Information Administration, Washington. <https://www.eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2017&cases=ref2017&sourcekey=0>. Accessed 14 Nov 2019
86. Office of Energy Efficiency and Renewable Energy. Building life cycle cost programs. Office of Energy Efficiency and Renewable Energy, Washington. <https://www.energy.gov/eere/femp/building-life-cycle-cost-programs>. Accessed 14 Nov 2019

87. U.S. Government Publishing Office. Energy independence and security act of 2007. U.S. Government Publishing Office, Washington. <https://www.gpo.gov/fdsys/pkg/PLAW-110publ140/pdf/PLAW-110publ140.pdf>. Accessed 14 Nov 2019
88. Department of the Treasury Internal Revenue Service. Proceedings of the 2018 instructions for form 1120. Department of the Treasury Internal Revenue Service, Washington. <https://www.irs.gov/pub/irs-pdf/i1120.pdf>. Accessed 14 Nov 2019
89. Scarboro M (2017) State corporate income tax rates and brackets for 2017. Tax Foundation, Washington. <https://files.taxfoundation.org/20170224134124/Tax-Foundation-FF542.pdf>. Accessed 14 Nov 2019
90. Coinnews Media Group LLC. US historical inflation rates: 1914-2019. <http://www.usinflationcalculator.com/inflation/historical-inflation-rates/>. Accessed 14 Nov 2019
91. SKR Consulting. General plan of operations: appendix 14, reclamation and closure plan. SKR Consulting, Anchorage. http://dnr.alaska.gov/mlw/mining/largemine/greenscreek/pdf/gc2014gpo14_rcp.pdf. Accessed 14 Nov 2019
92. HOMER Energy LLC. Generator fuel curve intercept coefficient. HOMER Pro 3.9, Boulder. https://www.homerenergy.com/products/pro/docs/3.9/generator_fuel_curve_intercept_coefficient.html. Accessed 14 Nov 2019
93. Farret FA, Simoes MG (2017) Integration of renewable sources of energy. Wiley, Chichester
94. Hatti M (2018) Artificial intelligence in renewable energetic systems: smart sustainable. Springer, Berlin
95. Zobaa-Ahmed F, Bansal-Ramesh C (2018) Handbook of renewable energy technology. World Scientific Publishing Company, Singapore
96. Design by Initiative LLC. Effects of low load operation on a diesel generating set. Design by Initiative LLC, Fayetteville. http://www.designbyinitiative.com/files/5314/2806/8039/Effects_of_low_load_running.pdf. Accessed 14 Nov 2019
97. Cummins. Power suite help. Columbus: Cummins. https://powersuite.cummins.com/PS5/PS5Content/HTML/common/Binary_Asset/docs/PowerSuite5.pdf. Accessed 14 Nov 2019
98. Innovus Power. Microgrid Power systems lowering the LCOE of hybrid systems. Innovus Power, Fremont. <https://d2oc0ihd6a5bt.cloudfront.net/wp-content/uploads/sites/837/2015/06/5-Mike-Wanebo-Innovus-Solutions-for-LCOE-Reduction-ACEF-June-2015.pdf>. Accessed 14 Nov 2019
99. Centolella P (2017) Estimates of the value of uninterrupted service for the mid-west independent system operator. https://hepg.hks.harvard.edu/files/hepg/files/voll_final_report_to_miso_042806.pdf. Accessed 14 Nov 2019
100. Lawton L, Sullivan M, Van Liere K, Katz A (2003) A framework and review of customer outage costs: integration and analysis of electric utility outage cost surveys. Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley
101. Johansson TB, Kelly H, Reddy AKN, Burnham L (1992) Renewable energy: sources for fuels and electricity, 2nd edn. Island Press, Washington, DC
102. Fu R, Feldman D, Margolis R, Woodhouse M, Ardani K (2017) U.S. solar photovoltaic system cost benchmark: Q1 2017. National Renewable Energy Laboratory, Denver
103. NC Clean Energy Tech Center. Database of state incentives for renewables and efficiency. NC Clean Energy Tech Center, Raleigh. <http://www.dsireusa.org/>. Accessed 14 Nov 2019
104. DSIRE. Business energy investment tax credit (ITC). N.C. Clean Energy Technology Center, Raleigh. <https://programs.dsireusa.org/system/program/detail/658>. Accessed 14 Nov 2019
105. DSIRE. Modified accelerated cost-recovery system (MACRS). N.C. Clean Energy Technology Center, Raleigh. <http://programs.dsireusa.org/system/program/detail/676>. Accessed 14 Nov 2019

106. Balfour J, Shaw M, Bremer-Nash N (2013) Advanced photovoltaic installations: the art and science of photovoltaics. Jones & Bartlett Learning, Burlington
107. Prasad D, Snow M (2005) Designing with solar power: a source book for building integrated photovoltaics (BIPV). CRC, Boca Ratón
108. Dobos AP (2014) PVWatts version 5 manual. National Renewable Energy Laboratory, Denver
109. NREL. NREL's PVWatts® calculator. <https://pvwatts.nrel.gov/index.php>. Accessed 15 Nov 2019
110. Marion B, Adelstein J, Boyle K, Hayden H, Hammond B, Fletcher T, et al (2005) Performance parameters for grid-connected PV systems. National Renewable Energy Laboratory, Denver
111. Deline C, Meydbray J, Donovan M (2016) Photovoltaic shading testbed for module-level power electronics: 2016 performance data update. National Renewable Energy Laboratory, Denver
112. Ryberg DS, Freeman J (2017) Integration, validation, and application of a PV snow coverage model in SAM. National Renewable Energy Laboratory, Denver
113. Mai T, Cole W, Krishnan V (2015) Impact of Federal tax policy on utility-scale solar deployment given financing interactions. Lawrence Berkeley National Laboratory, Berkeley
114. GTM Research/ESA. U.S. energy storage monitor: Q2 2017 executive summary. https://www.qualenergia.it/wp-content/uploads/2017/06/GTMR_US_Energy_Storage_Monitor_Q2_2017_Exec_Summary.pdf. Accessed 15 Nov 2019
115. Schmidt O, Hawkes A, Gambhir A, Staffell I (2017) The future cost of electrical energy storage based on experience rates. Nat Energy 2:17110
116. Wodd Mackenzie (2016) Grid-scale energy storage balance of systems 2015–2020: architectures, costs, and players. GTM research, January 2016. Wodd Mackenzie, Edinburgh
117. McLaren J, Gagnon P, Anderson K, Elgqvist E, Fu R, Remo T (2016) Battery energy storage market: commercial scale, lithium-ion projects in the U.S. National Renewable Energy Laboratory, Denver
118. DiOrio N, Dobos A, Janzou S (2015) Economic analysis case studies of battery energy storage with SAM. National Renewable Energy Laboratory, Denver
119. Glazie C, Geniès S (2013) Lithium batteries and other electrochemical storage systems. Wiley, Chichester
120. Soloveichik GL (2011) Battery technologies for large-scale stationary energy storage. General Electric Global Research, Niskayuna
121. Richmond R (2015) Lithium-Ion batteries for off-grid systems—are they a good match? http://www.righthandeng.com/hp153_pg86_richmond_liion_for_re.pdf. Accessed 15 Nov 2019
122. Rydh CJ, Sandén BA (2005) Energy analysis of batteries in photovoltaic systems. Part II: energy return factors and overall battery efficiencies. Energy Convers Manag 46(11–12):1980–2000
123. Patsios C, Wu B, Chatzinikolaou E, Rogers DJ, Wade N, Brandon NP, Taylor P (2016) An integrated approach for the analysis and control of grid connected energy storage systems. J Energy Storage 5:48–61
124. NREL. Federal tax incentives for energy storage systems. National Renewable Energy Laboratory, Denver. <https://www.nrel.gov/docs/fy18osti/70384.pdf>. Accessed 15 Nov 2019
125. Obi M, Jensen SM, Ferris JB, Bass RB (2017) Calculation of levelized costs of electricity for various electrical energy storage systems. Renew Sustain Energy Rev 67:908–920
126. McLaren J, Laws N, Anderson K, DiOrio N, Miller H (2019) Solar-plus-storage economics: what works where, and why? Electr J 32(1):28–46
127. Laws ND, Anderson K, DiOrio NA, Li X, McLaren J (2018) Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings. Renew Energy 127:896–909

128. Comello S, Reichelstein S (2016) The US investment tax credit for solar energy: alternatives to the anticipated 2017 step-down. *Renew Sustain Energy Rev* 55:591–602
129. Wang X, Kurdgelashvili L, Byrne J, Barnett A (2011) The value of module efficiency in lowering the levelized cost of energy of photovoltaic systems. *Renew Sustain Energy Rev* 15(9):4248–4254
130. Gagnon P, Cole WJ, Frew B, Margolis R (2017) The impact of retail electricity tariff evolution on solar photovoltaic deployment. *Electr J* 30(9):22–28
131. Bazen EF, Brown MA (2009) Feasibility of solar technology (photovoltaic) adoption: A case study on Tennessee’s poultry industry. *Renew Energy* 34(3):748–754
132. Chan G, Evans I, Grimley M, Ihde B, Mazumder P (2017) Design choices and equity implications of community shared solar. *Electr J* 30(9):37–41
133. Oueid RK (2019) Microgrid finance, revenue, and regulation considerations. *Electr J* 32(5):2–9
134. Swift KD (2013) A comparison of the cost and financial returns for solar photovoltaic systems installed by businesses in different locations across the United States. *Renew Energy* 57:137–143
135. Sovacool BK (2008) Renewable energy: economically sound, politically difficult. *Electr J* 21(5):18–29
136. Krupa J, Harvey LDD (2017) Renewable electricity finance in the United States: a state-of-the-art review. *Energy* 135:913–929
137. Sahu BK (2015) A study on global solar PV energy developments and policies with special focus on the top ten solar PV power producing countries. *Renew Sustain Energy Rev* 43:621–634
138. Augustine P, McGavisk E (2016) The next big thing in renewable energy: shared solar. *Electr J* 29(4):36–42
139. Liu X, O’Rear EG, Tyner WE, Pekny JF (2014) Purchasing versus leasing: a benefit-cost analysis of residential solar PV panel use in California. *Renew Energy* 66:770–774
140. Comello S, Reichelstein S, Sahoo A (2018) The road ahead for solar PV power. *Renew Sustain Energy Rev* 92:744–756

Footnotes

¹ In electricity grids, most of the connected loads are normally concentrated in distribution systems, which generally consist of radial feeders [16]. One consequence of the use of radial feeders is that many customers may be affected by the failure of a single component [16].

² Photovoltaic solar panels are normally mounted on covered roofs with an inclination of only 10–20° in order to reduce the loads due to wind and losses due to shadows. Although the azimuth and tilt can be adjusted at will, a photovoltaic panel on an inclined roof is usually installed directly on the roof surface.

³ The “DC to AC size ratio” would basically be the ratio between the nominal AC power of the inverter and the rated DC power of the collector field. The value that comes by default in the program is 1.10. This means that a collector field with a nominal power of 4 kW in DC would have an inverter with a rated power of 3.63 kW. In a system in which there is a high “DC to AC size ratio”, when the DC power of the collector field exceeds the INPUT nominal power of the inverter (in DC), the inverter will be in charge of limiting the output power of the collector field by increasing the input voltage to the inverters, which causes the operating point of the collector field to move along the curve (IV). The default value in the program (1.10) is reasonable for most installations. Although it is very large systems can reach up to 1.50, a typical value is between 1.10 and 1.25.

4 Mismatch means “mismatch” and that is the problem. The mismatching or mating effect occurs in many situations in the electrical world, all when several generators or transformers are joined in parallel or in series. Within the module there are usually about 60 cells grouped in series. As this group is made, the module will have some electrical or other parameters. Although this is in the hands of the designers of the installation, but of the manufacturers, it is convenient that the engineers who design them know these parameters. Imagine that a cloud or dirt make a module or a series work with different parameters than the others. We must take into account the amount of surface occupied by a solar garden. This is why the software takes this effect into account.

5 This effect can be caused due to the interaction of several factors, namely: The environmental conditions of the place, especially in hot and humid climates. The electrical conditions of the photovoltaic system, the greater the tension of the series (strings), the greater the possibility of appearance of the effect. The quality of the solar panel used in the installation. The quality of the solar panel cells in question.

6 MACRS is a methodology used to recover the capitalized costs of tangible properties that, over the years, reduce their value. Under this system, the capitalized cost is recovered throughout the life cycle of the tangible property through annual deductions (depreciation).

7 The cost of producing electricity would be the cost of the components of the battery system. This would include, for example, the inverters and the so-called System Balance (BOS, Balance of System), which would include elements such as solar cables, connectors, fuses, junction boxes and so on. Keep in mind that the amount of energy that a battery can store is determined by its capacity (kWh) while the charge or discharge rate is determined by its nominal power (kW). While the cost of the photovoltaic system is usually determined solely by its nominal power (kW), the storage costs are determined both by its capacity (kWh) and by its power (kW). The “electrical” components of the system [inverter, system balance (BOS)] are defined through an “electrical” metric (\$/ kW); while the “energetic” components of the system (for example, batteries) are defined through an “energy” metric (\$/kWh).

8 Depending on the state of charge (SOC), it was found that the efficiency of the electronic converter for a storage consisting of 100 kW / 50 kWh lithium ion batteries was around 96% for a state of charge of 30–100%.

9 When the state of charge of an ion-lithium battery falls below 20%, the voltage decreases rapidly, the ratio between the energy delivered with respect to the energy recovered from storage is reduced and heat is generated.

10 MACRS is a methodology used to recover the capitalized costs of tangible properties that, over the years, reduce their value. Under this system, the capitalized cost is recovered throughout the life cycle of the tangible property through annual deductions (depreciation).

Resilience Improvement in Office Buildings with Critical Loads

Enrique Rosales-Asensio¹, Miguel de Simón-Martín²,
David Borge-Diez² , Jorge Juan Blanes-Peiró² and
Antonio Colmenar-Santos³

(1) University of Las Palmas de Gran Canaria, Campus de
Tafira S/n, 35017 Las Palmas de Gran Canaria, Canary
Islands, Spain

(2) Departamento de Ingeniería Eléctrica y de Sistemas y
Automática, Escuela de Ingenierías Industrial e
Informática, Universidad de León, Campus de
Vegazana, s/n, 24071 León, Spain

(3) Departamento de Ingeniería Eléctrica, Electrónica,
Control, Telemática y Química Aplicada a la Ingeniería,
UNED, Juan del Rosal, 12-Ciudad Universitaria,
28040 Madrid, Spain

 **David Borge-Diez**
Email: dbord@unileon.es

Abstract

This chapter analyses the benefits from both a business-related and energy resilience perspectives provided by a microgrid based on photovoltaic solar

energy/electrochemical storage. We present a case study that demonstrates how a microgrid can be used to an office building not open to the general public (that is, for the exclusive use of office building employees). In this case study, we first identified how, by using distributed resources (in particular, photovoltaic solar panels and electrochemical storage), the microgrid life-cycle cost of energy can be reduced for a “normal” (connected to the electrical network) operation mode. Next, we evaluated how these technologies can be added to the microgrid to increase the resilience of the network—the resilience has been quantified based on the period length the microgrid is able to sustain an electrical consumer at an outage. It was found that, by adding photovoltaic solar energy and electrochemical storage, it was possible to extend the amount of time that the microgrid could survive a power cut from the current impossibility (= zero hours) to an average of four hours for the solar photovoltaic/electrochemical storage system proposed. Even in the event that there was a cut in the supply of the conventional electricity grid, the microgrid could continue feeding the loads of the office building not open to the public. We found that the microgrid could save \$112,410 in energy over the 20-year life cycle of the facility, while increasing the amount of time it can survive a power outage. The analysis carried out can be applied to other sites interested in quantifying the energy, economic and resilience benefits of the use of distributed resources based on renewable energies.

Keywords Energy resilience - Systems based on renewable energies - Solar energy - Electrochemical storage - Microgrids

Nomenclatures

AS Ancillary services
BDG Backup diesel generators
C Battery capacity
DR Discount rate
EB Energy balance
ED Energy demand
ECRC Energy capacity replacement cost
ECRY Energy capacity replacement year
EMS Energy Management System
FCI Federal corporate income
FS&L Federal, state, and local
GCM Grid connected mode
HETR Host effective tax rate
INOCT Installed normal operating cell temperature
LCC Life cycle cost
MACRS Modified Accelerated Cost-Recovery System
MSOC Minimum state of charge
NERC North American Electric Reliability Corporation
PCRC Power capacity replacement cost
PCRY Power capacity replacement year
PICM Power interruption cost model
PPR Peak power requirements
RP Reactive power
RTE Round trip efficiency
SoC State of charge
SL System losses

1 Introduction

In an electrical power system, resilience is characterized by the following four key elements: (1) prevention of interruption of power supply; (2) mitigation of the consequences of the interruption of the power supply; (3) reduction of response times needed to restore electricity, and (4) recovery of electricity supply [1]. Although policy makers have focused on the decarbonization of electricity generation for many years, some recent extreme weather events have led to an increase in attention to the resilience of the electricity sector [2]. Failures in the electrical grid that have to do with strong weather, electrical loads greater than the desired value, and safety breaches, have had as a result that, the ability of the electrical grid to perform its required functions under stated conditions for a specified time, is becoming more and more important [2]. Therefore, it is imperative to increase the availability of electricity supply in order to provide an adequate service during power outages and other emergencies [2]. Backup Diesel Generators (BDGs) are currently the most widely accepted option to provide energy when an outage occurs [3, 4]. However, renewable energies are progressively acquiring greater strategic importance in energy resilience [5]. This is mainly due to two causes:

- (a) First of all, and particularizing this research carried out to the case of the United States of America, this country has seen how seven of the ten most costly disasters that occurred during the 1980–2018 period have taken place in the last 13 years [6]. This demonstrates the fact that, given the changing environmental conditions, the current approaches and regulations for existing and future energy infrastructures may no longer be sufficient [7].
- (b) Second, the reduction in costs of solar photovoltaic technology has been “impressive” in recent years [8].

With regard to new and emerging electricity storage technologies, their potential cost reduction is equally significant [9].

Fuel supply interruptions are not only a theoretical vulnerability [10]. According to the “State of Reliability 2017” report [11] (from North American Electric Reliability Corporation—NERC), the lack of fuel was the second most important cause of forced outages of the generators; being the fourth most important cause by 2015 [11].

As a consequence of the above, the ability to maintain electrical service during a blackout; the maximization of the economic benefit of the facilities; and the integration of distributed resources that allow the system to effectively use energy, improve its stability (frequency, voltage), and meet the requirements of demand, is something that must necessarily go through the use of renewable energies [12]. On the other hand, BDGs, which are nearly inactive all the year, have proven to have a lower reliability than technologies used every day [13]. This circumstance has, in the case of large office buildings, important economic effects [13].

The use of distributed resources and electrochemical storage in microgrids can contribute in the (i) improvement of the reliability of the system [14, 15]; (ii) the improvement of the quality of energy [14, 15]; (iii) the provision of Ancillary Services (AS) [15]; (iv) the provision of Peak Power Requirements (PPR) by way of on-site generation [15]; (v) the provision of reactive power (RP) [15]; and (vi) the provision of an electricity supply in emergency situations [16]. As shown in [17], forming an electric island (=a microgrid) to sustain loads considered critical and increase the resilience of the installation is possible today by using standard equipment. Additionally, in last years some research works have proposed microgrids interesting innovations which turns feasible, for instance, to exchange the battery bank in the autonomous

polygeneration microgrid topology with hybrid capacitors [18], to reduce the risk of total system break-down, since a possible failure of some decentralized agents does not translate to total Energy Management System (EMS) failure [19], to optimize the operation of autonomous polygeneration microgrids [20], and to solve the multi-operation management problem in a typical microgrid with Renewable Energy Sources [21].

This chapter focuses on the role of renewable energies in reducing energy consumption; energy costs; and dependence with respect to the electrical grid of large office buildings not open to the public.

About 50 publications were reviewed for this chapter and, despite being a substantial and representative sample of the state-of-the-art, this number is not absolute. Some researchers have focused on investigating the design, implementation, and simulation of a hybrid microgrid testing facility, outlining different elements within it required to make a functional microgrid test system [22]; on proposing a power balancing strategy with smart grid interaction, aiming at reducing grid peak consumption [23]; on proposing a comprehensive approach for evaluating the performance of various Smart/Near-Zero Energy buildings [24]; or on develop, test and apply an optimization model to evaluate on-site renewable energy technologies with storage in buildings and assess optimal configurations for zero or nearly zero energy buildings [25].

From a deep survey of grey literature and updated literature related to the topic addressed here, it was possible to find that—even though there are plenty deal of different approaches—this chapter undoubtedly contributes to the pool of existing knowledge by proposing a methodology to quantify the benefits from both a business-related and energy resilience perspectives provided by a microgrid based on photovoltaic solar

energy/electrochemical storage (to our knowledge, so far not addressed specifically for large office buildings not open to the public). By performing this thorough literature review, we ensure the originality of the idea and method here presented. From this line of analysis, a much clearer insight of solar PV/electrochemical storage systems' benefits on the resiliency of similar office buildings not open to the public is gained (so far not explicitly shown to our knowledge in any scientific paper). Furthermore, the proposed method here presented improves analysis in the sense that a systematic and easy approach manages to make comparisons among different office buildings regardless of their sizes and locations.

Section 1 indicates the objectives of the research article and provides an adequate background, without going into detail in the literature or in the results obtained. Section 2 describes the methodology to quantify the economic and resilience benefits provided by renewable energies in microgrids, and summarizes assumptions and key inputs for the analysis to be carried out. Section 3 will first evaluate technologies that make smaller the LCC of the site under normal operation, connected to the electricity grid; Then, once the renewable resources are selected and optimally evaluated, carry out a series of stochastic simulations that analyze the performance of the micro-grid resulting from interruptions of random durations. Finally, Sect. 4 explores the significance of the results of the scientific article and introduces the major outcomes of the research carried out.

2 Material and Methods

This section describes the methodology used to quantify the economic and resilience benefits provided by renewable energy resources in microgrids, while

summarizing assumptions and key inputs for the analysis carried out.

2.1 Modeling Approach

2.1.1 The REopt Model

In this chapter, the REopt modeling platform [28] has been used in order to evaluate the renewable energy resources and storage technologies that minimize energy costs and increase the resilience of the microgrid studied.

Formulated as a linear program of mixed integers, this software resolves a problem in which no randomness is involved in the development of future states of the system in order to conclude which is the most favorable technology to be used, its size, as well as to propose a dispatching approach for selected components within a group of candidates; in such a way that the loads are satisfied at all times through a minimum life cycle cost [29]. The cost of the energy life cycle includes the costs of ED, capital costs, profits and tax incentives, and the operation and maintenance costs associated with photovoltaic solar panels and electrochemical storage (if the use of them decreases the life cycle cost of energy) [29]. The software models the economic aspects for all the years of the analysis period of N years, optimizing only the EB for the beginning 365 days.¹ It is supposed that all projects are built immediately and that they begin to be operational in year 1² [30]. REopt also provides the optimum delivery strategy based on a business-related perspective to operate the recommended technologies at maximum economic efficiency [31].

2.1.2 Assessment of the Economic Benefits of Renewable Energies and Electrochemical Storage

Solar energy systems are an option increasingly widely used by those electricity consumers (customers) who want to reduce their monthly bill and generate electricity on-site [30]. When combined with storage in the form of batteries, the benefits of solar energy is higher [30]. A scheme that includes solar energy and electrochemical storage can provide a variety of services, from benefits in the form of resilience such as emergency electric power to economic benefits such as savings in electricity bills [30]. The design of a hybrid scheme of solar energy and electrochemical storage will depend on the expected function (or functions) of the system [30]. In general terms, schemes based on photovoltaic solar energy and electrochemical storage can be grouped into those designed to provide energy isolated from the electricity grid and those designed to operate connected to the electricity grid [30]. Solar energy and electrochemical storage facilities can potentially provide high benefits from both a business-related and an electrical resilience perspective [30]. REopt model was used to simulate a case in which the office building not open to the public continues to acquire its electricity from the electricity grid. REopt was also used to optimize a scheme based on renewable energies/electrochemical storage, where the size and operation of the system are optimized through the model. In this case, it will be evaluated if the renewable energy systems are advantageous supposing they operate on a GCM, and if they are also capable of feeding electrical loads during power grid failures.

2.1.3 Assessment of the Increase in Resilience Due to Renewable Energies and Electrochemical Storage

Apart from the economic benefits, another important aspect when evaluating microgrids that have to feed critical loads is the quantitative evaluation of the additional

resilience obtained through the proposed scheme [31]. In this section, a methodology will be described to quantify what would be the increase in the capacity to supply energy to the loads of an office building not open to the public through the introduction of renewable distributed energy resources. Through the use of REopt, the scheme based on renewable energies is evaluated to obtain the greatest economic benefit for an operation connected to the electricity grid, in which the renewable energy system can reduce the expenses related to the purchase of electricity, reduce demand peaks, and carry out an energy arbitration.

As a measure for resilience we will use the term “survivability”, which is defined as the probability of having electricity continuously available during a power outage until it is reestablished within t units of time after the interruption of the electrical network has taken place [32]. It should be taken into account the fact that the likeliness of happening an outage depends on the variation in the electrical load versus time, C ; the electrochemical storage SoC when the interruption of the supply occurs; as well as on its duration and the battery management strategy [32].

By using a conventional BDGs and a constant quantity of on-site combustible, the “survivability” changes depending on the power interruption length of time. For example, for a critical facility such as a hospital or an airport, the “survivability” would typically be 1 (100%) for the first 24 h of a power outage (assuming a sufficient amount of fuel is available), falling rapidly as the supply runs out of fuel. For a hybrid system based on renewable energies, the “survivability” of the aforementioned hospital or airport due to power cuts of longer durations would be greater due to their ability to satisfy the electricity requirements of the loads that were previously exclusively powered by backup diesel generators. However, for those facilities considered

as “non-critical” (such as office buildings not open to the public) maintaining backup generators which are idle most of the time of the year might not be advantageous from a business-related perspective.

To assess the increase in terms of electrical resilience provided to a scheme based exclusively on renewable energies (such as the office building evaluated in this research), the “survivability” is calculated solely taking into account renewable energies and electrochemical storage. By default, it is normally assumed that the electricity grid is 100% reliable, which means that it is capable of providing an infinite amount of electricity at any time [33]. However, in an electrical resilience analysis, what is usually done is to inject a random number of failures in the model to evaluate the ability of the scheme to sustain interruptions in the electrical grid [33]. A model that can evaluate the cost of a random interruption of the electricity supply from the available statistics is necessary to carry out an adequate cost-benefit analysis [36, 37]. The most widely used PICM is the “customer damage function” [38], which models an average interruption cost for each type of customer as a function of duration. However, there are other factors besides the duration that also affect the cost of the interruption of the power supply [36, 37]. For example, the time and day of the week in which the power outage occurs, or the season of the year are also important [36, 37]. REopt [28] takes these circumstances into account when carrying out the optimization of the scheme [29–31].

2.2 Inputs of the Model

The modeled site is a supposed office building not open to the public located in the city of Palmdale (California), with a total area of 60,000 ft² (about 5575 m²).

2.2.1 Electricity Tariff

Like any company, this supposed office building located in the city of Palmdale (California) requires having a reliable energy to avoid (or mitigate) the potential losses in the event that there is a power cut. Considering McKenney et al. [37], the average load has been assumed to be approximately 110 kW, varying from a minimum of 85 kW to a maximum of 180 kW in summer. The total annual energy consumption is 1000,000 kWh [33].

The site is in an unregulated market that is fed by Southern California Edison [through the TOU-8 CPP rate (2–50 kV)] [40] for supply. It has been assumed that, for the year 2017, the costs related to electricity amounted to \$178,500. Some information regarding the tariff used for the office building not open to the public is shown in Table 1.

Table 1 Electric tariff used. Source: [41]

Time-Of-Use—General Service—Large: TOU-8 CPP (2 kV-50 kV)		
Fixed charge (first meter) (\$/month)	319.47	Fixed charges
Seasonal/monthly demand charge structure (Rate \$/kW)	14.88	Demand
<i>Time of use demand charge structure</i>		
Period 1 (Tier 1; Rate \$/kW)	0	Demand
Period 2 (Tier 1; Rate \$/kW)	6.41	Demand
Period 3 (Tier 1; Rate \$/kW)	23.24	Demand
Demand reactive power charge (\$/kVAR)	0.51	Demand
<i>Tiered energy usage charge structure</i>		
Period 1 (Tier 1; Rate \$/kWh)	0.06426	Energy
Period 2 (Tier 1; Rate \$/kWh)	0.08397	Energy
Period 3 (Tier 1; Rate \$/kWh)	0.05902	Energy
Period 4 (Tier 1; Rate \$/kWh)	0.08222	Energy
Period 5 (Tier 1; Rate \$/kWh)	0.1351	Energy

According to the tariffs currently available for Southern California Edison [40]:

Option R of this Schedule (Schedule TOU-8) is available to customers with demands not exceeding annual peak demands of four (4) MW and who install, own, or operate solar, wind, fuel cells, or other eligible onsite Renewable Distributed Generation Technologies as defined by the California Solar Initiative (CSI) or the Self-Generation Incentive Program (SGIP). Eligible systems must have a net renewable generating capacity equal to or greater than 15 percent of the customer's annual peak demand, as recorded over the previous 12-months... Participation on this rate option is limited to a cumulative installed distributed generation output capacity of 400 MW for all eligible rate groups.

This tariff is favorable for photovoltaic solar energy because most of the charges related to electricity occur during the peaks of the generation of this technology. It is less favorable to electrochemical storage because there are no charges related to "Time-of-Use demand".

2.2.2 Technologies Evaluated

The following elements were included in the model for consideration: electrical grid, photovoltaic solar energy, and electrochemical storage. Although other technologies could also play an important role in the near future, today they are, among the most "respectful" with the environment, the most widespread and at a lower cost for buildings, so they will be the only ones that will be evaluated in this chapter.

- (a) **Electrical grid.** It has been assumed that the national electricity grid can essentially provide an unlimited amount of electricity and energy [43]. It has been

supposed that the utility has not capital nor operation and management costs and that the only expenditure is the energy from the grid [44].

- (b) **Photovoltaic solar energy.** REopt uses capacity factors (per hours) to model the production of each renewable technology during each hour of the year [41]. In the case of photovoltaic solar energy, the hourly capacity factors are obtained by REopt from the PVWatts database [46] for the specific location and assuming a typical orientation and efficiency of the photovoltaic panel [45]. The following assumptions were made:

Solar resource data site: Lat, Lon: 34.57, −118.1

These coordinates correspond to that of the city of Palmdale (California).

Module Type: Standard.

Table 2 shows some data about module types material, efficiency, and temperature coefficient of power for some module types.

Table 2 Module types material, efficiency, and temperature coefficient of power

Module type	Cell material	Approximate nominal efficiency (%)	Module cover	Temperature coefficient of power
Standard	Crystalline Silicon	15	Glass	−0.47%/°C
Premium	Crystalline Silicon	19	Glass with anti-reflective coating	−0.35%/°C
Thin film	Thin film	10	Glass	−0.20%/°C

Source Reference [40]

Array Type: Fixed (roof mount).³

System Losses (%): 14.08.

SLs stands on values from Table 3. They have been calculated as follows:

Table 3 Values used to calculate SLs divided into categories

Category	Value (%)
Soiling	2
Shading	3
Snow	0
Mismatch	2
Wiring	2
Connections	0.5
Light-induced degradation	1.5
Nameplate rating	1
Age	0
Availability	3

Source Reference [36]

$$100\% * [1 - (1 - 0.02) * (1 - 0.03) * (1 - 0.02) * (1 - 0.02) * (1 - 0.005) * (1 - 0.015) * (1 - 0.01) * (1 - 0.03)] = 14.08\%$$

Annual performance degradation: 0.5

The amount of electricity produced by the photovoltaic panels is proportional to the capacity factor of each site [29]. Due to the fact that their production tends to decrease throughout their useful life, REopt only optimizes the production of one year, and then calculates a profile of

annual productions that has a degradation of 0.5%/year [47] for the period of analysis.

Tilt angle (deg): 34.57

Azimuth angle (deg): 180

DC to AC Size Ratio: 1.1

Inverter Efficiency (%): 96

Ground Coverage Ratio: 0.4

Average annual retail electricity rate: \$0.160 W-year

PVWatts[®] downloads a retail electricity rate for the rate type chosen based on the latitude and longitude of the solar resource data [46]. The rate data corresponds to the year 2012 and was taken from Ventyx Research Inc. and the Energy Information Agency (EIA) [46].

System capital cost (\$/kW): \$2000 [48]

(c) **Electrochemical storage.** REopt models electrochemical batteries as a “reservoir”, in which the energy produced at a given moment can be consumed in another [29].⁴

Characteristics of lithium-ion batteries are assumed as follows [26]:

Energy capacity cost (\$/kWh): \$500

Power capacity cost (\$/kW): \$1000

ECRP (\$/kWh): \$230

ECRY: 10

PCRC (\$/kW): 460

PCRY: 10

Rectifier efficiency (%): 96%

Round trip efficiency (%): 97.5%

Inverter efficiency (%): 96%

Total AC-AC RTE: 89.9%

MSOC (%): 20%

Initial state of charge (%): 50%

2.2.3 Resilience Assessment

As a result of the modeling conducted by the software used, it can be applied to reproduce the effect of power cuts [27]. This allows the assessment of a number of components available in the model, all along the GCM (the great majority of the year) and during the interruptions of the electrical grid. This ability to perform has a particular significance for distributed resources, since they can be productive during GCM and support electrical loads during a network outage (while conventional backup generators can only operate during an outage due to the legal requirements relating to air quality) [27].

2.2.4 Economic Assumptions

In this chapter it has been assumed that the proposed technologies would be installed immediately and that they would produce energy throughout the evaluated analysis, which, following the “2017 Annual Technology Baseline”—NREL [49], has been assumed to be of 20 years. An increase rate of electricity costs⁵ of 2.6% per year [50]⁶ [51],⁷ and 2.5% per year⁸ [49]⁹ [51]¹⁰ [52]¹¹ for operation and maintenance costs has been assumed. Based on guidance for regulatory benefit-cost analyses from FORTISBC ENERGY UTILITIES [53], all utility costs and operation and management costs incurred in the out-years are discounted to the present. Following the NREL 2017 Annual Technology Baseline and Standard Scenarios [49], the electric sector’s historical nominal weighted average cost of capital (8.1%), has been used as nominal discount

rate to evaluate the scheme proposed (it should be taken into account that DR requirements might change considerably among promoters).

It should be taken into account that solar PV *stimulus* are accessible at the FS&L level. Following [53] a federal 30% investment tax credit has been supposed.¹² Solar projects are eligible for accelerated depreciation deductions over a five-year period [55].¹³ This circumstance has also been included in the model. A 40% HETR (15–35% for FCI taxes + 0–12% state corporate income taxes) [49, 56, 57] has been supposed. The energy components of the battery system are supposed to be replaced at the year 10 of the project lifecycle [58].

Model key inputs are summarized in Appendix 5.

3 Results and Discussion

First, technologies that would lessen the LCC of the microgrid for normal operation, connected to the electricity grid, were evaluated. Under this approach, the distributed resources (photovoltaic solar energy/electrochemical storage) of the microgrid are optimized to maximize the economic benefits for an operation connected to the electricity grid. Despite the fact that these technologies can increase the time at which the microgrid can cope with a power cut, this circumstance is not considered in the optimization process. Once these technologies are optimized, stochastic simulations that will analyze the performance of the resulting micro-grid in the event of supply cuts of random durations are carried out. Acting in this way, and despite the fact that resilience was not really a criterion for optimization, the REopt software is able to quantify the resilience of the microgrid.

As indicated in Table 4 (Appendix 1) and Table 5 (Appendix 3), the office building is able to minimize its

energy cost by installing a 282 kW solar photovoltaic system, and an electrochemical storage of 29 kW of nominal power and 55 kWh of capacity for the TOU-8 CPP tariff (2–50 kV)].

Table 4 Results summarizing the economic viability of PV and battery storage at the large office buildings not open to the public evaluated^{14 15 16}

Recommended solar installation size ¹⁷	282 kW (PV size)
Recommended battery power and capacity ¹⁸	Battery power: 29 kW Battery capacity: 55 kWh
Potential life cycle savings (20 years) ¹⁹	\$112,410

Source Own elaboration

Table 5 Results showing show how doing business as usual compares to the optimal case

	Business as usual	Optimal case	Difference
<i>System size, energy production, and system cost</i>			
PV size (kw)	0	282	282
Annualized PV energy production (kWh)	0	490,590	490,590
Battery power (kW)	0	29	29
Battery capacity (kWh)	0	55	55
DG system cost (Net CAPEX + O&M)	\$0	\$321,186	\$321,186
Energy supplied from grid in year 1 (kWh)	1000,000	572,718	427,282
<i>Year 1 utility cost—before tax</i>			
Utility energy cost	\$79,088	\$43,438	\$35,651
Utility demand cost	\$74,239	\$50,116	\$24,124
Utility fixed cost	\$0	\$0	\$0
Utility minimum cost adder	\$0	\$0	\$0
<i>Life cycle utility cost—after tax</i>			

	Business as usual	Optimal case	Difference
Utility energy cost	\$573,698	\$315,092	\$258,605
Utility demand cost	\$538,523	\$363,533	\$174,990
Utility fixed cost	\$0	\$0	\$0
Utility minimum cost adder	\$0	\$0	\$0
<i>Total system and life cycle utility cost—after tax</i>			
Life cycle energy cost	\$1112,221	\$999,811	\$112,410
Net present value	\$0	\$112,410	\$112,410

Source Own elaboration

In accordance with Table 7 (Appendix 5), the initial cost resulting from installing 282 kW of photovoltaic solar energy would be \$564,000, while the cost of electrochemical storage to be installed would be approximately \$29,000.²⁰ According to Table 5, photovoltaic solar energy would be able to generate 49% of the energy demanded by the office building. REopt calculates the solar photovoltaic energy scheme in such a way that it is able to minimize the charges related to the energy consumed. Although it “only” generates 49% of the energy consumed in the office building, part of that energy generated by the photovoltaic panels is produced when electricity is more expensive, so that the microgrid is able to sell it at a high price and to acquire electricity from the grid when the costs are lower. As a consequence of the microgrid scheme, utility energy costs would be reduced from \$573,698 to \$315,092 (see Table 5, Appendix 3). Current site life cycle energy cost would be of \$111,221, whereas the proposed scheme would be \$999,811 (see Table 5; Appendix 3). As a consequence, net present value of the investment would be of \$112,410 (see Table 5, Appendix 3).

Figure 2 (Appendix 2) shows how photovoltaic solar panels and electrochemical storage work together (while at

the same time acquiring electricity from the electricity grid), in order to meet the lowest possible costs. The microgrid uses electricity from the electricity grid during night hours when electricity prices are low and photovoltaic solar panels are not generating electricity. During the day, the solar panels are able to satisfy all the demanded energy, and the excess of electricity coming from the photovoltaic panels are used to load the electrochemical storage or to export that electricity to the grid. It should be noted how the electrochemical storage is strategically discharged between 15:00 h. and 18:00 h. because the production of electricity from solar photovoltaic panels is not able to satisfy all the demand of the office building (see Fig. 2, Appendix 2). Because the capacity of the electrochemical storage is limited in comparison to the load of the office building, its impact is small. Said that, it is able to provide some savings through a small reduction in peak demand.

For the optimization of the microgrid considered²¹ and for an energy resilience optimization, the proportion of usual demand to be satisfied at the time of an electrical interruption of service has been considered to be of a 50% (see Table 7, Appendix 5). Because there will inevitably be periods in which photovoltaic generation is not able to satisfy all the demand [60–65], electrochemical storage will be responsible for satisfying these charges until the generation from the solar photovoltaic panels can again feed them in full, or even that the state of charge of the battery reaches a lower limit in which the load is satisfied exclusively through the electrical grid.

To evaluate the repercussion of the considered scheme on the resilience of the microgrid, power cuts were simulated in the network with durations between zero days and two weeks, which would occur randomly throughout the year. In order to calculate the probability of surviving a

power cut, all simulated cuts were divided into 24-h periods (see Fig. 3, Appendix 4). The proportion of power cuts that the microgrid could sustain for each 24-h period is also shown in Fig. 3. From Fig. 3 it is possible to see how adding 282 kW of photovoltaic solar energy and an electrochemical storage of 29 kW of nominal power and 55 kWh of capacity to the office building, the amount of time that the microgrid would survive a cut of electricity would extend from the current 0 h to 4 h, with a 40% probability.

An example of the operation strategy of the microgrid is presented in Appendix 2 (Figs. 1 and 2). From B.2 it can be seen how the electrical grid satisfies the loads of the office building during the night. In the morning, the sun rises and the photovoltaic solar panels begin to generate electricity and to charge the electrochemical storage until the photovoltaic solar generation and the SoC of the electrochemical storage are high enough to satisfy the loads of the office building without the need to use the electrical grid. The load is then transferred to the photovoltaic solar panels/electrochemical storage. Note from Fig. 2 (Appendix 2) how, from 7:00 am, the excess of photovoltaic generation is first used to charge electrochemical storage and that “surplus” electricity is exported to the electric grid. In the afternoon, the generation of solar photovoltaic panels decreases, until reaching the point (around 16:00 h., see Fig. 2), in which photovoltaic solar energy cannot fully satisfy the load of the office building. From 18:00 h. all the electricity consumed comes exclusively from the electricity grid (see Fig. 2).

4 Conclusions

The results of the analysis carried out in this research demonstrate how a scheme consisting of 282 kW of photovoltaic solar energy and batteries of a nominal power of 29 kW and 55 kWh capacity would be able to produce a

saving of \$35,651 per year in costs of energy. Throughout the 20 years of the life cycle supposed for the facility, the proposed microgrid would be able to generate a potential savings of \$112,410. The system would be able to generate 49% of the energy required by the office building for a normal operation connected to the electrical grid. As a result of the integration of the photovoltaic solar panels/electrochemical storage in a microgrid, the site would obtain an extra resilience of four hours compared to the current situation. There are additional benefits of a microgrid based on renewable energies that have not been considered in the analysis of the LCC carried out in the research presented here, which does not provide an economic value to this added “survivability”. During a power outage, the costs incurred by it can be large for a business. This value, despite not being included in the economic analysis, should be considered in the decision of the investment. The profile of the electricity demand, the electricity tariff, the costs of the technologies used, the incentives, as well as the solar resource play a critical role in determining the viability of renewable energies and electrochemical storage, so each scheme must be evaluated in a particular way.

Appendix 1

See Table [4](#).

Appendix 2: Dispatch Strategy Optimized

Figure [1](#) shows the dispatch strategy optimized by REopt Lite for a month (June) (Fig. [2](#)).

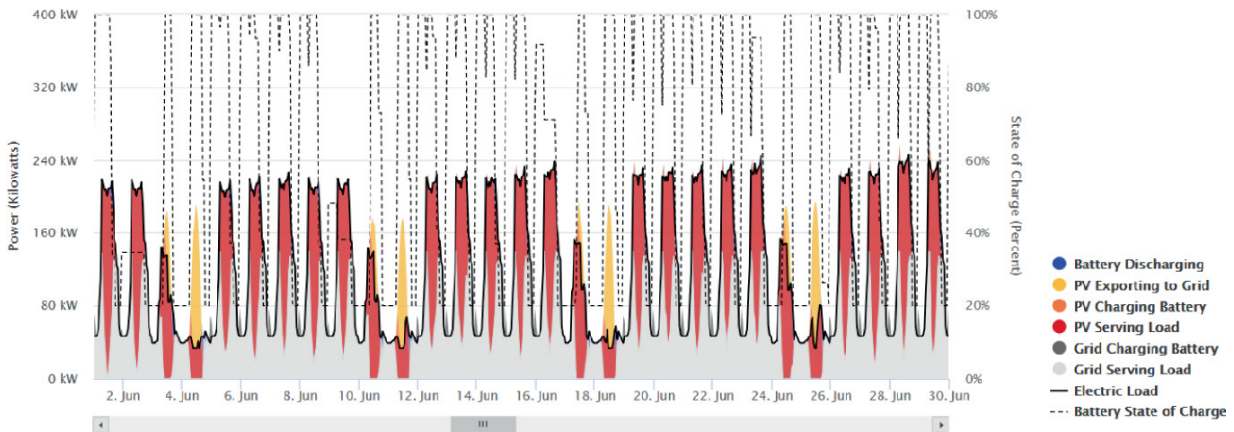


Fig. 1 Dispatch strategy optimized by REopt Lite for a month (June).
Source Own elaboration

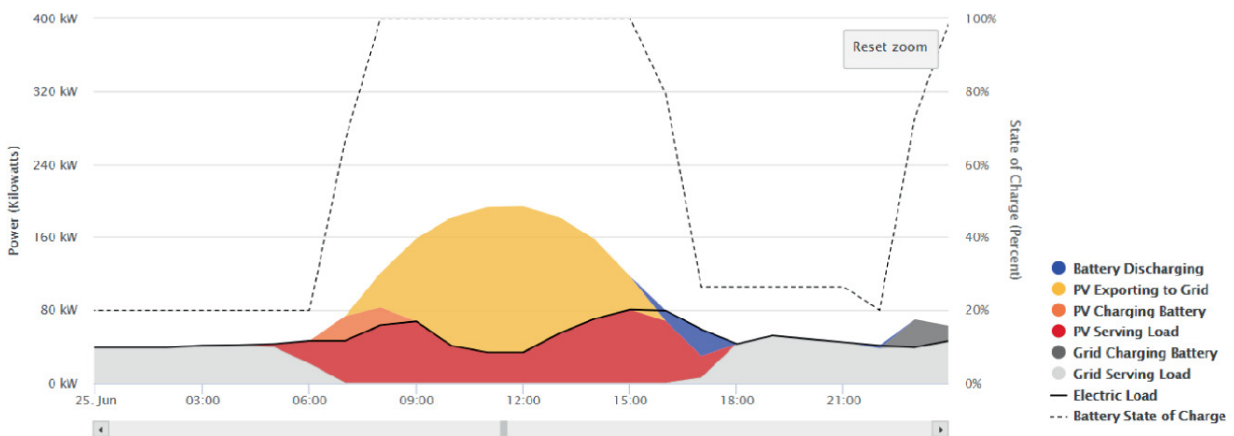


Fig. 2 Dispatch strategy optimized by REopt Lite for a day (25th June).
Source Own elaboration

Appendix 3: Results Comparison

See Table 5.

Appendix 4: Outage Simulation

See Table 6 and Fig. 3.

Table 6 Evaluation of the amount of time that your system can survive grid outages

Average resiliency ²²	4 h
----------------------------------	-----

Minimum resiliency ²³	0 h
Maximum resiliency ²⁴	18 h

Source Own elaboration

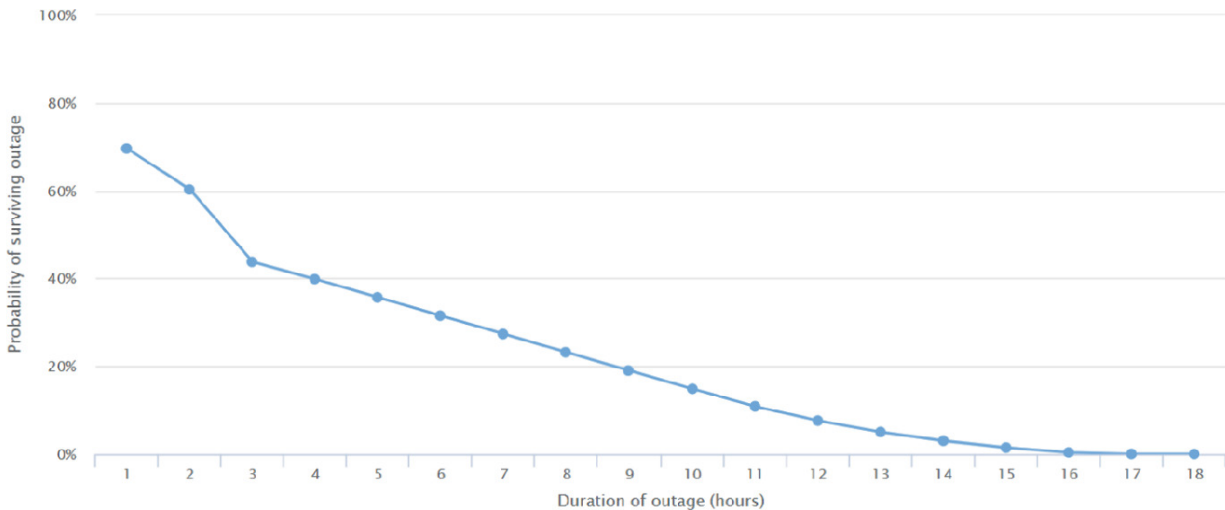


Fig. 3 Duration of outage (hours) versus probability of surviving outage.
Source Own elaboration

Appendix 5: Model Inputs

See Table 7.

Table 7 Inputs used to obtain the results

<i>Site and utility</i>	
Site name	
Site location	Palmdale, CA
Latitude	34.579434
Longitude	−118.116461
Land available (acres)	Unlimited
Roofspace available (sq ft)	Unlimited
Load profile	Simulated
Type of building	Office-Large

Annual energy consumption (kWh)	1000,000
URDB rate	Southern California Edison Co Time-Of-Use—General Service—Large: TOU-8 CPP (2–50 kV) last updated 2016-02-10
Do you want to evaluate PV and/or battery?	Both
<i>Financial</i>	
Analysis period (years)	20
Host discount rate, nominal (%)	8.1%
Host effective tax rate (%)	40%
Electricity cost escalation rate, nominal (%)	2.6%
O&M cost escalation rate (%)	2.5%
<i>PV</i>	
System capital cost (\$/kW)	\$2000
O&M cost (\$/kW per year)	\$16
Minimum size desired (kW DC)	0
Maximum size desired (kW DC)	Unlimited
Module type	Standard
Array type	Rooftop, Fixed
Array azimuth (deg)	180
Array tilt (deg)	5
DC to AC size ratio	1.1
System losses (%)	14%
Net metering system size limit (kW)	0
Federal percentage-	30%

based incentive (%)	
Federal maximum incentive (\$)	Unlimited
Federal rebate (\$/kW)	\$0
Federal maximum rebate (\$)	Unlimited
State percentage-based incentive (%)	0%
State maximum incentive (\$)	Unlimited
State rebate (\$/kW)	\$0
State maximum rebate (\$)	Unlimited
Utility percentage-based incentive (%)	0%
Utility maximum incentive (\$)	Unlimited
Utility rebate (\$/kW)	\$0
Utility maximum rebate (\$)	Unlimited
Production incentive (\$/kWh)	\$0
Incentive duration (years)	1
Maximum incentive (\$)	Unlimited
System size limit (kW)	Unlimited
MACRS schedule	5
<i>Battery</i>	
Energy capacity cost (\$/kWh)	\$500
Power capacity cost (\$/kW)	\$1000
Energy capacity replacement cost (\$/kWh)	\$230
Energy capacity replacement year	10

Power capacity replacement cost (\$/kW)	\$460
Power capacity replacement year	10
Minimum energy capacity (kWh)	0
Maximum energy capacity (kWh)	Unlimited
Minimum power capacity (kW)	0
Maximum power capacity (kW)	Unlimited
Rectifier efficiency (%)	96%
Round trip efficiency (%)	97.5%
Inverter efficiency (%)	96%
Minimum state of charge (%)	20%
Initial state of charge (%)	50%
Allow grid to charge battery	Yes
Total percentage-based incentive (%)	0%
Total rebate (\$/kW)	\$0
MACRS schedule	7
<i>Resilience</i>	
Outage start	
Outage duration (hours)	
Critical load factor	50%

Source Own elaboration

References

1. Elder B (2015) Docket No. 39732—notice of inquiry and workshop to examine issues related to the value of renewable and distributed energy resources in preparations for the 2016 Georgia Power Company Integrated Resource Plan (IRP). Keyes, Fox and Wiedman LLP, Cary
2. Lubetsky J (2014) Combined heat and power provides energy resiliency to medical facilities: improvements to current tax credits can keep operations running, save fuel and money. The Pew Charitable Trusts, Philadelphia
3. Doosan Fuel Cell America (2014) Critical & clean power: 7 reasons why PureCell® fuel cell systems are the right choice. Doosan Fuel Cell America, South Windsor
4. Thornton A, Rodríguez-Monroy C (2011) Distributed power generation in the United States. *Renew Sustain Energy Rev* 15:4809–4817 [[Crossref](#)]
5. International Energy Agency (2015) Making the energy sector more resilient to climate change. International Energy Agency, Paris
6. National Centers for Environmental Information (2018) Billion-dollar weather and climate disasters: table of events. National Centers for Environmental Information, Silver Spring. Accessed 22 May 2018. <https://www.ncdc.noaa.gov/billions/events/US/1980-2018>
7. World Energy Council (2016) World energy perspectives: the road to resilience 2016. World Energy Council, London
8. IRENA. Renewable Power Generation Costs in 2017. Abu Dhabi: International Renewable Energy Agency; 2018.
9. IRENA (2017) Renewable power: sharply falling generation costs. International Renewable Energy Agency, Abu Dhabi
10. Popik TS (2017) Testimony of the foundation for resilient societies: United States of America before the federal energy regulatory commission—reliability technical Conference Docket No. AD17-8-000. In: Proceedings of the reliability technical conference, 22 June 2017
11. NERC (2017) State of reliability 2017. North American Electric Reliability Corporation, Atlanta
12. Members of the Vermont General Assembly (2017) Re: energy storage report pursuant to act 53 of 2017. State of Vermont, Department of Public Service, Montpelier
13. Olinsky-Paul T (2013) Using State RPSS to promote resilient power at critical infrastructure facilities. Clean Energy States Alliance, Montpelier

14. Moghaddam AA, Seifi A, Niknam T, Pahlavani MRA (2011) Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy* 36(11):6490–6507. ISSN 0360-5442
15. Pepermans G, Driesen J, Haeseldonckx D, Belmans R, D’haeseleer W (2005) Distributed generation: definition, benefits and issues. *Energy Policy* 33(6):787–798. ISSN 0301-4215, <https://doi.org/10.1016/j.enpol.2003.10.004>
16. U.S. Department of Energy (2007) The potential benefits of distributed generation and rate-related issues that may impede their expansion: a study pursuant to section 1817 of the Energy Policy Act of 2005. U.S. Department of Energy, Washington
17. Fenimore T, Gould A, Wright L (2017) Implementing a microgrid using standard utility control equipment. In: 2017 70th Annual conference for protective relay engineers (CPRE), College Station, TX, pp 1–9
18. Kyriakarakos G, Piromalis D D, Arvanitis KG, Dounis AI, Papadakis G (2015) On battery-less autonomous polygeneration microgrids: Investigation of the combined hybrid capacitors/hydrogen alternative. *Energy Conv Manage* 91:405–415. ISSN 0196-8904, <https://doi.org/10.1016/j.enconman.2014.12.027>
19. Karavas CS, Kyriakarakos G, Arvanitis KG, Papadakis G (2015) A multi-agent decentralized energy management system based on distributed intelligence for the design and control of autonomous polygeneration microgrids. *Energy Convers Manage* 103:166–179. ISSN 0196-8904, <https://doi.org/10.1016/j.enconman.2015.06.021>
20. Karavas C-S, Arvanitis K, Papadakis G (2017) A game theory approach to multi-agent decentralized energy management of autonomous polygeneration microgrids. *Energies* 10:1756 [[Crossref](#)]
21. Moghaddam AA, Seifi A, Niknam T, Pahlavani MR (2011) Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy* 36(11):6490–6507. ISSN 0360-5442. <https://doi.org/10.1016/j.energy.2011.09.017>
22. Leskarac D, Moghimi M, Liu J, Water W, Lu J, Stegen S et al (2018) Hybrid AC/DC Microgrid testing facility for energy management in commercial buildings. *Energy Build* 174:563–578
23. Sechilariu M, Wang B, Locment F (2013) Building-integrated microgrid: Advanced local energy management for forthcoming smart power grid communication. *Energy Build* 59:236–243

- [Crossref]
24. Kampelis N, Gobakis K, Vagias V, Kolokotsa D, Standardi I, Isidori D et al (2017) Evaluation of the performance gap in industrial, residential & tertiary near-Zero energy buildings. *Energy Build* 148:58–73
[Crossref]
 25. González-Mahecha RE, Lucena AFP, Szklo A, Ferreira P, Vaz AIF (2018) Optimization model for evaluating on-site renewable technologies with storage in zero/nearly zero energy buildings. *Energy Build* 172:505–516
[Crossref]
 26. NREL (2018) Renewable energy integration & optimization. National Renewable Energy Laboratory, Denver. Accessed 23 May 2018. <https://reopt.nrel.gov/tool>
 27. NREL (2017) Renewable energy optimization (REopt). National Renewable Energy Laboratory, Denver. Accessed 23 May 2018. <https://reopt.nrel.gov/tool/REopt%20Lite%20Web%20Tool%20User%20Manual.pdf>
 28. NREL (2014) REopt: a platform for energy system integration and optimization. <https://www.nrel.gov/docs/fy14osti/61783.pdf>. National Renewable Energy Laboratory, Denver. Accessed 23 May 2018
 29. Cutler D, Olis D, Elgqvist E, Li X, Laws N, DiOrio N et al (2017) REopt: a platform for energy system integration and optimization. National Renewable Energy Laboratory, Denver. Accessed 23 May 2018. <https://www.nrel.gov/docs/fy17osti/70022.pdf>
 30. Utah Clean Energy (2017) Solar and storage for energy and resiliency: a guide for consideration. Utah Clean Energy, Salt Lake City
 31. Chaudry M, Ekins P, Ramachandran K, Shakoor A, Skea J, Strbac G et al (2009) Building a resilient UK energy system. In: Working paper 31 March 2009: REF UKERC/WP/ES/2009/023. UK Energy Research Centre, London
 32. Jongerden MR, Hüls J, Remke A, Haverkort BR (2016) Does your domestic photovoltaic energy system survive grid outages? *Energies* 9(9):736
[Crossref]
 33. Simpkins T, O'Donnell, C (2017) Optimizing battery sizing and dispatching to maximize economic return. In: Battcon 2017 international stationary battery conference; 8–10 May 2017, Orlando, FL
 34. Baik S, Morgan MG, Davis AL (2018) Providing limited local electric service during a major grid outage: a first assessment based on customer willingness to pay. *Risk Anal* 3(2):272–282
[Crossref]

35. Wei Y, Ji C, Galvan F, Couvillon S, Orellana G, Momoh J (2016) Non-stationary random process for large-scale failure and recovery of power distribution. *Appl Math* 7:233–249
[Crossref]
36. Teansri P, Bhasaputra P, Pattaraprakorn W (2011) Development composite customer damage function using the customer survey-based method for power system reliability planning. In: The 8th electrical engineering/electronics, computer, telecommunications and information technology (ECTI): Association of Thailand—Conference 2011; 17–19 May 2011; Khon Kaen, Thailand, pp 844–847
37. McKenney K, Guernsey M, Ponoum R, Rosenfeld J (2010) Commercial miscellaneous electric loads: energy consumption characterization and savings potential in 2008 by building type. Lexington, IAX LLC
38. Gammon T (2017) Evaluation of electrical feeder and branch circuit loading: phase I. Fire Protection Research Foundation, Quincy
39. Luo X, Hong T, Chen Y, Piette MA (2017) Electric load shape benchmarking for small- and medium-sized commercial buildings. Lawrence Berkeley National Laboratory, Berkeley
[Crossref]
40. Southern California Edison. Rate Schedule TOU-8. https://www.sce.com/NR/rdonlyres/4393B684-6D2A-49F0-8359-85DC4CD1D679/0/091022_TOU8_Fact_Sh.... Accessed 25 May 2018
41. OpenEI. Basic information. https://openei.org/apps/IURDB/rate/view/56bbe096682bea7fa5c3145d#1__Basic_Information. Accessed 25 May 2018
42. Southern California Edison. Schedule TOU-8 Time-of-Use—general service—large. <https://www.sce.com/NR/sc3/tm2/pdf/ce54-12.pdf>.
43. Inversin AR (2000) Mini-grid design manual. National Rural Electric Cooperative Association, Arlington
44. Wood L, Hemphill R, Hemphill RC, Howat John, Cavanagh R, Borenstein S (2016) Recovery of utility fixed costs: utility, consumer, environmental and economist perspectives. Future Electric Utility Regulation Advisory Group, Berkeley
45. Richards A, Deprizio J, Anderson K, DiOrio N, Elgqvist E, Simpkins T (2016) Portfolio analysis of renewable energy opportunities. In: SCTE/ISBE cable-tec expo; 26–29 Sept 2016; Philadelphia, Pennsylvania
46. NREL. PVWatts calculator. <https://pvwatts.nrel.gov/>. Accessed 28 May 2018

47. National Academies of Sciences (2017) Utilizing the energy resource potential of DOE lands. The National Academies Press, Washington, DC
48. NREL. Distributed generation renewable energy estimate of costs. <https://www.nrel.gov/analysis/tech-lcoe-re-cost-est.html>. Accessed 28 May 2018
49. NREL (2017) Annual technology baseline (ATB), <https://data.nrel.gov/files/71/2017-ATB-data.xlsm>. Accessed 9 June 2018
50. EIA. Annual Energy Outlook 2017 table: energy prices by sector and source case: reference case | Region: United States, <https://www.eia.gov/outlooks/aeo/data/browser/#/?id=3-AEO2017&cases=ref2017&sourcekey=0>. Accessed 9 June 2018
51. Lavappa PD, Kneifel JD, O'Rear EG (2017) Energy price indices and discount factors for life-cycle cost analysis—2017 annual supplement to NIST handbook 135. NIST, Gaithersburg
52. COINNEWS MEDIA GROUP LLC. Historical inflation rates: 1914–2018. <http://www.usinflationcalculator.com/inflation/historical-inflation-rates/>. Accessed 9 June 2018
53. EES Consulting. FortisBC Energy Utilities Review of System Extension Policies March 2013, https://www.fortisbc.com/About/RegulatoryAffairs/GasUtility/NatGasBCUCSubmissions/Documents/150630_FEI%202015%20System%20Extension%20Application_FF.pdf. Accessed 9 June 2018
54. U.S. Internal Revenue Service. Business Energy Investment Tax Credit (ITC), <http://programs.dsireusa.org/system/program/detail/658>. Accessed 9 June 2018
55. U.S. Internal Revenue Service. Modified accelerated cost-recovery system (MACRS), <http://programs.dsireusa.org/system/program/detail/676>. Accessed 9 June 2018
56. Department of the Treasury Internal Revenue Service (2017) 2017 Instructions for form 1120 U.S. corporation income tax return. Department of the Treasury Internal Revenue Service, Washington
57. Scarboro M (2017) State corporate income tax rates and brackets for 2017. Tax Foundation, Washington
58. Smith K, Saxon A, Keyser M, Lundstrom B, Cao Z, Roc A (2017) Life prediction model for grid-connected Li-ion battery energy storage system. In: 2017 American control conference (ACC), 24–26 May 2017, Seattle, WA
59. Sandia National Laboratories. Module 11—cost estimation. <http://sites.middlebury.edu/dallen/files/2016/05/Cost-Estimating-for-Advanced-Microgrids-1.pptx>. Accessed 10 June 2018

60. Beccali M, Finocchiaro P, Ippolito MG, Leone G, Zizzo G et al (2018) Analysis of some renewable energy uses and demand side measures for hotels on small Mediterranean islands: a case study. *Energy* 157:106–114 [[Crossref](#)]
 61. Clegg S, Mancarella P (2018) Integrated electricity-heat-gas modelling and assessment, with applications to the Great Britain system. Part II: transmission network analysis and low carbon technology and resilience case studies. *Energy*. <https://doi.org/10.1016/j.energy.2018.02.078>
 62. Ma W, Xue X, Liu G (2018) Techno-economic evaluation for hybrid renewable energy system: application and merits. *Energy* 159:385–409 [[Crossref](#)]
 63. Fonseca JA, Schlueter A (2013) Novel approach for decentralized energy supply and energy storage of tall buildings in Latin America based on renewable energy sources: case study—informal vertical community Torre David, Caracas—Venezuela. *Energy* 53:93–105 [[Crossref](#)]
 64. Weber C, Shah N (2011) Optimisation based design of a district energy system for an eco-town in the United Kingdom. *Energy* 36(2):1292–1308 [[Crossref](#)]
 65. Johansson B (2013) Security aspects of future renewable energy systems—A short overview. *Energy* 61:598–605 [[Crossref](#)]
-

Footnotes

1 Following [[22](#)] the model achieves an energy balance between consumption and generation during each period of time by creating and dispatching an optimal combination of renewable generation and energy storage. Although the REopt economic model considers an analysis period of N years, it is assumed that the energy consumption and production are constant for all years in such a way that the optimal balance of energy achieved for year 1 remains valid for the subsequent years in the analysis period. In making this assumption, the present value of the total energy costs for the next N years can be determined by increasing the current energy costs (using an increase rate for electricity) and then discounting those costs at present by using an appropriate discount rate.

2 Following [[23](#)] REopt assumes a perfect prediction of all future events, including weather conditions and charges.

3 Following [21] (...) The roof mount option is typical of residential installations where modules are attached to the roof surface with standoffs that provide limited air flow between the module back and roof surface. For roof mount systems, the installed normal operating cell temperature (INOCT) is 50 degrees Celsius, which corresponds roughly to a three or four inches standoff height.

4 Following [23] REopt does not explicitly model the “chemistry” of batteries, but imposes heuristic restrictions that are designed to ensure that the battery operates within the manufacturer's specifications. REopt imposes limits for the minimum load status, loading and unloading rates, and the number of cycles per day. The model is capable of selecting and dimensioning both the capacity of the battery in kWh and the power provided in kW.

5 The nominal electricity cost escalation rate is provided explicitly in the EIA's Annual Energy Outlook and can also be calculated implicitly by combining the NIST Handbook's real electricity cost escalation rates with expected inflation rates [21].

6 The EIA predicts a 2.6% average nominal annual commercial electricity escalation rate from 2017 to 2037 in their reference case scenario, assuming an inflation rate of 2.1%. Regional variation yields a range of annual electricity cost escalation rates from 1.7 to 3.5% [21].

7 The average real commercial electricity cost escalation rate across the US over the period 2017–2037 was 0.52%, as described in table Cb-5 of the NIST Handbook 2017. More detailed projections for rates across the various regions of the US are available in the Handbook in tables Cb-1 through Cb-4. Five-year average electricity cost escalation rates over the period 2017–2037 for the different regions of the US range from –0.2 to 1% [21].

8 O&M costs are assumed to escalate at inflation rate [21].

9 NREL analyses assume an inflation rate of 2.5% [21].

10 Federal projects use an inflation rate of -0.6% [21].

11 Lists monthly US inflation rates from 1914 to 2017. Inflation rate in July 2017 listed as 1.7%. Since 2010, inflation rates have ranged from -0.2 to 3.9% [21].

12 Following [48] this investment tax credit is available to solar projects regardless of size, with no maximum incentive for solar technologies.

13 The Consolidated Appropriations Act, signed in December 2015, extended the “placed in service” deadline for bonus depreciation. Equipment placed in service before January 1, 2018 can qualify for 50% bonus depreciation. Equipment placed in service during 2018 can qualify for 40% bonus depreciation. And equipment placed in service during 2019 can qualify for 30% bonus depreciation [49].

14 These results assume perfect prediction of both solar irradiance and electrical load. In practice, actual savings may be lower based on the ability to accurately predict solar irradiance and load, and the battery control strategy used in the system [21].

15 The results include both expected energy and demand savings. However, the hourly model does not capture inter-hour variability of the PV resource. Because demand is typically determined based on the maximum 15-minute peak, the estimated savings from demand reduction may be exaggerated. The hourly simulation uses one year of load data and one year of solar resource data. Actual demand charges and savings will vary from year to year as load and resource vary [21].

16 Photovoltaic system performance predictions calculated by PVWatts[®] include many inherent assumptions and uncertainties and do not reflect variations between PV technologies nor site-specific characteristics

except as represented by inputs. For example, PV modules with better performance are not differentiated within PVWatts[®] from lesser performing modules [21].

17 Measured in kilowatts of direct current, this recommended size minimizes the life cycle cost of energy at the site [21].

18 This system size minimizes the life cycle cost of energy at the site. The battery power and capacity are optimized for economic performance [21].

19 This is the net present value of the savings (or costs if negative) realized by the project based on the difference between the life cycle energy cost of doing business as usual compared to the optimal case [21].

20 Control costs associated with providing controls to the office building [53] [(a) costs to install communications infrastructure necessary for microgrid controls, including monitoring and protection; (b) local as well as overall supervisory controls involved with synchronization, start-up and outputs of generators; and (c) devices involved in detecting and clearing faults which may occur within microgrids] are not included in the optimization conducted by REopt.

21 An independent system, where the photovoltaic solar generators/electrochemical storage operate independently, and in which the solar panels/electrochemical storage feed the loads of the office building during part of the time (usually during the day) and transfer the loads to the grid when the solar resources and the state of charge of the battery are inadequate (usually during the night).

22 The average amount of time that the system can sustain the critical load. 8760 outage simulations are run—one for each hour of the year—and the Average Resiliency is calculated as the average time survived during the simulated outages. The battery state of charge at the start of each outage is determined by the economically optimal dispatch strategy. This means that if the battery was being used for peak shaving prior to the outage, it may be at a low state of charge when the outage occurs. Note that in order to gain this

resiliency, the PV + battery must be installed as an island-able system. This incurs additional costs above a typical grid-connected system that are not included in the economics presented here. Additional components required may include a manual or automatic transfer switch, critical load panel, and additional controls capabilities in the inverter for islanded operation [21].

23 *The minimum amount of time that the system can sustain the critical load. 8760 outage simulations are run—one for each hour of the year—and the Minimum Resiliency is calculated as the minimum time survived during the simulated outages. The battery state of charge at the start of each outage is determined by the economically optimal dispatch strategy. This means that if the battery was being used for peak shaving prior to the outage, it may be at a low state of charge when the outage occurs. Note that in order to gain this resiliency, the PV + battery must be installed as an island-able system. This incurs additional costs above a typical grid-connected system that are not included in the economics presented here. Additional components required may include a manual or automatic transfer switch, critical load panel, and additional controls capabilities in the inverter for islanded operation [21].*

24 *The maximum amount of time that the system can sustain the critical load. 8760 outage simulations are run—one for each hour of the year—and the Maximum Resiliency is calculated as the maximum time survived during the simulated outages. The battery state of charge at the start of each outage is determined by the economically optimal dispatch strategy. This means that if the battery was being used for peak shaving prior to the outage, it may be at a low state of charge when the outage occurs. Note that in order to gain this resiliency, the PV + battery must be installed as an island-able system. This incurs additional costs above a typical grid-connected system that are not included in the economics presented here. Additional components required may include a manual or automatic transfer switch, critical load panel, and additional controls capabilities in the inverter for islanded operation [21].*

Resilience Improvement in PreCOVID-19 Medical Centers

Alexis Lagrange¹, Miguel de Simón-Martín², Alberto González-Martínez², Stefano Bracco³ and Enrique Rosales-Asensio⁴ 

- (1) Département Génie Électrique Informatique Industrielle, Université du Havre, 34 rue Boris Vian, 76610 Le Havre, France
- (2) Department of Electrical, Systems and Automatics Engineering, School of Mines Engineering, Universidad de León, Campus de Vegazana s/n, 24071 León, Spain
- (3) Department of Naval, Electrical, Electronics and Communications Engineering, Università degli Studi di Genova, Savona Campus, Via Opera Pia, 16145 Savona, Italy
- (4) University of Las Palmas de Gran Canaria, Campus de Tafira s/n, 35017 Las Palmas de Gran Canaria, Canary Islands, Spain

 **Enrique Rosales-Asensio**
Email: enrique.rosales@ulpgc.es

Abstract

This manuscript proposes to study different cases that require the use of renewable energies in addition to diesel generators and energy storage systems with the aim of increasing the resilience of a microgrid feeding critical facilities. The aim of the work here presented is to quantify the benefits provided by an improvement of the energy resilience that could be achieved by installing a microgrid in a hospital fed by renewable energy sources. The microgrid will use a scheme based on solar PV in addition to diesel generators and an energy storage system based on electrochemical batteries. First, it has been evaluated how the implant of the microgrid increases the resilience of the power supply when a power failure occurs, considering that the main application in a hospital, even in the event of breakdowns, is to ensure the continuity of the surgical procedures and safely store drug stocks. Thus, these has been defined as the critical loads of the system. The components sizes have been optimized by considering both economic profitability but also the resilience capacity, observing that, by installing solar photovoltaic modules, Li-ion batteries and diesel generators, the microgrid could save approximately \$440,191 over a 20-year life cycle of the facility (both considering the mitigation of energy provide by the power grid and the avoided losses during probable power services interruptions), while increasing the minimum resilience of the installation more than 34 h.

Keywords Energy resilience – Hospital – Solar photovoltaics – Microgrids – Batteries

1 Introduction

Microgrids can be defined as small grids with the ability to operate autonomously, independently of the conventional power grid [1]. Because of its autonomy, it can be found in a number of end-uses such as military bases, hospitals or university campuses. Microgrids have the ability to isolate themselves from the power grid when a power outage occurs. Then, they continue to supply their critical loads without interruption, which is of great importance for critical facilities. This chapter concerns in particular with the implantation of microgrids in hospitals, which are considered critical facilities that must guarantee electrical energy services for certain critical processes, such as surgery procedures or drugs storage.

Energy resilience has become vital in recent years as a result of many successive natural disasters. In the US, it has been found that power cuts due to the absence of an effective energy resilience policy has caused substantial economic losses in the last times. In particular, since 1980, on average, six disasters have exceeded \$1 billion dollars per year [2]. The consequences are much more dramatic and add to this heavy toll: loss of production in industries and safety in critical facilities. One solution to this problem might be to set up a Renewable Energy Hybrid System (REHS) microgrid comprising photovoltaic panels, batteries and diesel generators. It has been shown that, in some cases, the use of diesel generators might not be appropriate because they have not worked during periods of major disasters (when test phases showed the opposite). This was the case, for example, during Hurricane Sandy at Coney Island Hospital, where patients had to be evacuated due to the lack of functioning diesel generators [3]. But the failure of diesel generators has another cause: refills of fossil fuels add an uncertainty to the facility [2].

In other countries, such Kuwait or Egypt, the installation of photovoltaic panels has been proved as a means to reduce the pressure on power plants and meet the growing demand for electricity [4, 5]. The solution would avoid, on the one hand, the increase in the use of fossil fuels and, on the other hand, crises in electricity production. The consequences are also catastrophic for the country's industrial, social and economic sectors. As a result, the main international challenge will be to design green electrical systems that will not harm the environment [6]. However, there are a number of barriers that hamper the installation of microgrids [5]. In this case, energy support policies to reduce the investment costs and promote a faster implementation has been proved to be successful in some regions, such as Sicily (in Italy) [7].

Nowadays, in the US, hospitals' energy consumption represents nearly 5.5% of the total consumption of the country [1]. A potential hospital microgrid could assess electricity prices from the grid, and possibly “buy” electricity when its cost is low [1], and conversely, re-sell electricity when its cost would be high. In this case, intraday “*electrical hours*” have a great deal of influence on electricity. In the scientific literature, it has been shown that the establishment of microgrids has been promoted by favorable aid policies [8–11]. Other analyses also reveal the physical aspect to be considered because of the existing weaknesses in the

system: the presence of a transitional regime of the generators might, in some circumstances, lead to the complete collapse of the microgrid [12]. In addition, the various strategies that can be implemented to increase and boost resilience were investigated. According to [13–16], it will be necessary to set up self-sufficient microgrids by implementing the appropriate number of renewable energy sources (this design is a result of an “*electrical point of view*” of electrical systems adapted to extreme disasters). Lastly, the fight against cyber-attacks should neither be overlooked [17, 18].

This manuscript consists of three other sections. The following section brings together all the elements for analyzing the economic benefits and advantages of resilience with renewable energies. In this section the parameters to be entered during the simulation will be presented. The third section will be based on a series of simulations on a real case study. Finally, the last section will summarize the obtained results and the main authors’ conclusions.

2 Materials and Methods

This section explains the approaches addressed by *REopt*® [19] and the comparison between other software tools that can conduct a number of simulations related to the topic here addressed. The last part details the different families of inputs offered by the aforementioned software.

2.1 REopt® Model as a Modeling Approach

With *REopt*® [19], the economic viability of the joint use of solar PV, Li-ion batteries and diesel generators will be evaluated. The simulation system can also calculate the length of time that the system provides power to the site in the event of a power outage [20]. It should be noted that the model only provides technical and economic estimates of the various installations. As a consequence, it will be necessary to refer to decision-making strategies for investments at a later stage [20].

At this stage, these assumptions are sufficient for a first estimation. It should be noted that *REopt*® helps the facilities’ owners to find the “*optimal*” size for the microgrid facilities considering a scenario that minimizes the Levelized Cost of Electricity (*LCOE*). Thus, it evaluates the costs of the energy demand (ED), capital costs, profits, tax incentives and the operation and maintenance costs [20].

2.2 Comparisons Between Different Models

Depending on the software to be used, a number of simulations at different scales to assess the resilience of systems (residential, regional and/or district modelling) can be conducted. As shown in Table 1, *REopt*® is able to conduct simulations at all of the aforementioned levels.

Table 1 Evaluation of a number of simulation models implemented on different software tools

	Simulation	Optimization	Photovoltaics	Wind Energy	Biomass Energy	Battery Storage	Residential Modelling	District Modelling	Regional Modelling	Consecutive Technology Modelling	Finance	Performance	Free?	Capability of modelling large plants	Beginner Tool	Advanced Tool
SAM																
CREST																
PVWatts																
Pvsyst																
Windographer																
WindPro																
RETScreen																
Helioscope																
REopt																
HOMER																
Gatecycle																
ReEDS																
EnergyPlan																
KomMod																

Green cells mean that the software provides the corresponding feature in the column, while the red color means the opposite. Adapted from [21]

Performance models simulate energy efficiency with system configurations entered by the user. These different models can help to plan system sizes to meet energy objectives, reduce *LCOE*, and minimize carbon emissions.

It can be seen from Table 1, that *REopt*® has a large number of possibilities that other software could not accomplish. Green cells represent the features that can be used [21]. On the other hand, the red cells represent the features that cannot be used by the different software tools [21]. In our case, resilience can be optimized. The other simulations, on the whole, cannot achieve this objective.

As far as renewable energies are concerned, *REopt*® allows simulations to be carried out on a photovoltaic system, wind generators (currently with a beta version), and energy storage through batteries. From all the above, it is clear that *REopt*® will allow us to model the behavior of the system thus formed. It is now necessary to detail the different inputs that make up the simulation software to be used. Even though other software could have been used to conduct similar simulations and extend the assessments conducted to other locations different to the US, it has as a counterpart the fact that it is not an open-source software such as *REopt*® is.

2.3 Model Inputs

2.3.1 Location and Electricity Distributor

As case study to run the simulations, it has been selected a representative facility in California (US). The actual area of the site is 320,000 square feet which corresponds to 30,000 square meters [22].

With regard to the electricity distributor, the “*net metering*” is, in fact, an agreement between the electricity distributor and the consumer. In this case, when surplus electricity is produced, credits are granted and transferred to the

consumer who will only pay the net amount. Renewable installations may be affected by this pricing method. Currently in California the only limits imposed are that the maximum capacity must not exceed 1 MW; and that the share of renewable energy must be 5% of the use of electricity from the conventional electricity grid. In our simulation, we will assume that the studied installation will not be affected by net metering. It should be noted that this depends on the legislation that is adopted in each country or state [23].

2.3.2 Simulated Workload Profile

The simulated building will be evaluated over a complete year with an estimated consumption of 4900 MWh/year, according to statistic values for the US and this sort of buildings. The critical load factor, which in this case has been considered of 50%, has been estimated in order to include the store drugs devices, average surgical procedures electricity demand, other non-interruptible loads (life support systems) and part of lighting and power supplies.

2.3.3 Financial Criteria

The analysis period will be conducted for a time length of 20 years. This period analysis shall also consider, the equipment lifetime. Table 2 summarizes the increase in operation and maintenance costs over the last three years between 2017 and 2019, respectively. This corresponds to the so-called operation and maintenance (*O&M*) cost escalation rate and these values are expressed in %. In the last column (*Avg*) it can be observed that costs increased by 2.5% on average in this period. Then, a 2.5% yearly *O&M* cost increment will be considered in the performed simulations.

Table 2 Percentage increase in inflation of operating and maintenance costs

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG
2017	+2.5	+2.7	+2.4	+2.2	+1.9	+1.6	+1.7	+1.9	+2.2	+2.0	+2.2	+2.1	+2.1
2018	+2.1	+2.2	+2.4	+2.5	+2.8	+2.9	+2.9	+2.7	+2.3	+2.5	+2.2	+1.9	+2.4
2019	+1.6	+1.5	+1.9										

Source COINNEWS MEDIA GROUP LLC [24]

2.3.4 Resilience

For resilience, three separate assumptions will be made about the duration of the interruption of electricity distribution: 8, 16 and 24 h. These times are designed for hospitals to size the generators to feed their critical loads for a minimum of 8 h—and, at best, 24 h of assistance [25].

With regard to the day and time of the outage, June 21st and December 21st, days of summer solstice and winter solstice respectively, will be selected as critical days for the evaluation, as they represent both extremes of sunlight duration and thus, photovoltaic production. Second, two possible outage times will be considered in the analysis: at 2 a.m. and at 5 p.m.

The type of interruption chosen is considered to be severe, occurring only once during the life time of the project. This allows us to simulate and quantify the behavior of the microgrid in the event of a major disaster.

REopt® will include the presence of three diesel generators. For the conducted simulations, it has been assumed that each diesel generator had a nominal power of 400 kW—so, the total of the nominal power would be 1200 kW. It will also be assumed that the amount of fuel available will be 680 gallons or 2575 L [26]. In this case, and as a safety measure, emergency supply by diesel generators have been designed into three independent units to guarantee a minimum of 400 kW in case of failure of two units.

On the other hand, a value of \$100 per unserved kWh price has been considered as the cost of the unserved energy. This value depends on many factors that must be considered with care, including the power grid topology (radial or meshed), the supplied energy loads, the effects of a blackout in the feeded process, etc. Very little work has been done to incorporate the Value of Lost Load (VoLL) in the design of microgrids, although some approaches can be seen for sizing resilient microgrids to survive a design-outage [27]. In this case, the methodologies presented in [28–30] have been considered to approximate the VoLL as a function of the energy not served by the microgrid. It should be noticed that the unavailability of medical services is very costly and the toll then increases for public services that depend on hospitals and have to reimburse the affected sectors. In addition, health and safety effects are visible such as looting and vandalism [29], but in our study these side effects have been neglected as first approach.

2.3.5 Photovoltaic System

For the conducted evaluations a number of entries have considered, including different losses sources for the photovoltaic production: (i) dust that may accumulate over the life of the project, (ii) shadows that may form on solar panels, (iii) losses in diodes and connections, (iv) general ageing of the system, and (v) losses induced by light. Total losses have been estimated to be 14%.

2.3.6 Energy Storage by Batteries

Battery system design and dispatch strategies differ depending on the use-case and the value streams that are being tapped [31]. A value of 20% will be recorded for Minimum State of Charge (*MSoC*). When the battery, especially for Li-ion batteries, reaches this value, the voltage at its terminals decreases so rapidly that the efficiency is significantly affected [32]. In this case, it has been considered that the power grid can, in some cases, charge the batteries system if necessary.

3 Results

The work which follows takes up a series of simulations carried out with the *REopt*® software. The next step was to evaluate the performance of the grid and the different technologies through the various scenarios presented in the “*Materials and Methods*” section.

The first observation we can make is about charging the batteries. In fact, batteries are charged from the energy supplied when the electricity cost is minimal. The price is minimal between midnight and 1:00 a.m. in the morning, as illustrated in Fig. 7. Figure 2 shows a charging process at 8 p.m.; whereas Fig. 5 does the same at 6 a.m. In general, batteries are charged when the State of Charge (*SoC*) falls to a 20% (this value is a result of the state of complete

discharge of the batteries that we considered when entering the simulation inputs). Only in Figs. 5 and 7 can be seen that batteries are charged when the SoC is about 80 and 60%, respectively taking advantage of the surplus of PV energy. In the same way, in this scenario, we are also facing durations where the battery is being used during the day.

A similar scenario is presented in Figs. 5 and 7. There are however some small differences between these two curves. These two graphs correspond to the same dates, that is to say, the June 21st, but with a cut-off time of 8 and 16 h respectively. Nothing should change since we are before the expected outage. Figure 5 shows a peak between 7 a.m. and 8 a.m. that allows loads to be powered; whereas Fig. 7, at the same time, allowed batteries to be charged from energy solar resources.

The duration of the disconnection seems to have an impact on the previous behavior of the microgrid thus formed. Remarkable values between 5 a.m. and 4 p.m. for “Grid Serving Load” column of Tables 8 and 10 are shown in red. The results obtained on the same day are different even if it is before the power outage. However, there are differences of up to 100.3 kW at 7 a.m. and 18.4 kW at 10 a.m. The difference observed slightly changes the appearance of the simulation results according to Figs. 5 and 7. However, the software loads the consumption profiles for the year 2017. Moreover, these two graphs allow us to deduce a second outcome: the significant decrease in energy consumption is “picked” from the electrical grid. In Table 8, shown in purple with a variation of 100 kW, the SoC of the battery is optimized. We have seen earlier that the grid is a means of charging batteries when the costs are lower. The differences in values, however, which are small in both cases, are very marginal compared to the case studied previously (in red).

Figures 2 and 4 minimize the use of diesel generators to lessen their potential impact on the environment and partially address supply and distribution issues. In Fig. 2, the dedicated use is 7 h while in Fig. 4 the corresponding duration is almost 6 h. This saves 1 and 2 h of operation in a row. In one hour, about 220 kWh energy from diesel generators are consumed for the first case; and 233 kWh for the second one, according to both Tables 5 and 7, respectively. These savings will be important because diesel generators, after 8 a.m., have to power more loads (assuming that, in this case, photovoltaic modules would not be able to operate). The time of usage of diesel generators is reduced because solar resources are available at that time. Afterwards, these two scenarios should be put in context because one takes place in winter, according to Fig. 2; whereas the other case (Fig. 4) is in summer. The main reason for reducing in this case the use of diesel generators is that solar energy is available and it is able to supply the power loads. In winter, the fuel is used and consumed until 10 a.m., which marks the end of the power outage from the conventional grid. We are likewise in the case where the solar resources are insufficient compared to summer.

Figure 6 highlights a scenario where the solar resource is strongly present at the time the power outage has already occurred as it represents the summer solstice (June 21) and, thus, it is observed that the system is able to provide the energy needed to charge the batteries system and, on the other hand, to export surplus energy to the power grid.

The aim of this study case is to study the share from PV to feed the loads, the energy used to charge the batteries and the energy exported to the power grid. A

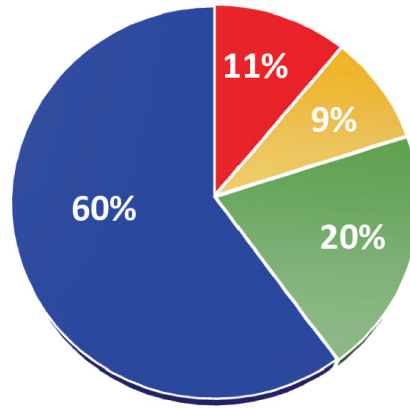
thorough analysis of these different values shows that from 7 a.m. onwards, the battery stores the remaining energy to increase its SoC from 70 to 100%. This can be seen in Table 9. The rest of the day, from 8 a.m. onwards, the power provided to the loads remains at around 400 kW. The remaining energy is exported to the power grid at a time when the profit of the resold energy would be maximum. Between 11 a.m. and 1 p.m., the share of exported power becomes greater than the share of energy consumed. *REopt*[®] considers that the best scenario in the event of power outages is to supply the majority of solar energy to the microgrid during the day. For the case studied, the solar energy that supplies the loads is kept constant from 8 a.m. to 3 p.m.

The battery will decrease its SoC until 20%, when the Sun is about to set. Figures 8 and 9 show the same type of reasoning, but with a much longer break time: 24 h instead of 16 h. However, it should be noted that Fig. 6 contains an intermediate discharge level that is only understandable because of the compensation for the increase in energy required for hospital needs. It also exists because of the appearance of the Sun is about to set. At about 10 p.m., the batteries can no longer be used. This is present, in a smaller quantity in Fig. 9. Figure 3 shows a situation where all solar resources are being exploited to supply the different loads. Even if this represents a winter scenario, Figs. 8 and 9 can charge the batteries and resell the electricity thus recovered. The difference here comes from the fact that there is a high demand for electricity, which Figs. 8 and 9 may reveal since the disconnection of the traditional grid is already underway.

Of all the above studies, the battery provides energy when solar resources are not operational. Figures 4, 5 and 7 shows the second alternative, in the event that energy demand becomes too high. It should be remarked that the proposed simulation, for diesel generators, are supposed to operate without malfunctions. As explained above, in the Introduction section, failures might occur during disasters. It should be considered that the use of a diesel generator requires increased supervision, especially when batteries and photovoltaic panels will not be able to supply energy [31].

In hospitals, loads are rather reactive in nature and it becomes necessary to have a stable transition, especially in voltage. It will be also necessary to consider, if necessary, the installation of capacitors that will increase the reactive reserve [31]. Due to this likely installation is not considered by the simulation, costs from this example may be higher than reality.

Finally, it is also necessary to consider in the most general way, the cost to which the project would be put in case of dysfunctions. This is shown in Fig. 1, considering the example of batteries. The project assessed would cost \$883,427. It can be seen on the aforementioned figure that the batteries would have a specific weight of 60% of the final cost of the project, which represents approximately \$530,056. The Development/Software Costs and Hardware parts simultaneously represent the last third of the project cost. It should be reminded, however, that, for the project studied, the decision model provided by *REopt*[®] does not allow to approximate the cost of such an investment. It is therefore inevitable that investments of this type of technology are more expensive according to the Fig. 1.



■ Development/Software Costs ■ Engineering Procurement Construction (EPC) ■ Hardware ■ Battery

Fig. 1 Project cost breakout when using Li-ion batteries. Source [28]

4 Conclusions

The research here presented estimates the savings that could be achieved over the lifecycle of a critical microgrid, in this case, considering a hospital as case study. Evaluations conducted in this research paper presented a breakdown among the different end-uses of the electricity produced by solar PV, i.e., battery charging, energy supplied to the microgrid loads, and energy resold to the electricity grid. For the proposed scheme, and for the city of Palmdale (California), it was noted that most of the energy used by the loads of the hospital were obtained from solar PV. Batteries are used when the Sun is about to set or when the demand for electricity becomes high. The development carried out has made it possible to establish the schedules during which electricity is the cheapest. On days when electricity demand is high, all photovoltaic energy will be used to power the various loads. It can therefore be concluded that, with high solar resources and, for the electricity tariff studied, the addition of solar PV makes it possible to increase the resilience of a microgrid in the event of power outages. From a given load profile, it is therefore possible to determine how the microgrid will behave. All of this will reduce dependence on the use of diesel generators in a hospital. A further research might be to assess a microgrid based on the priorities between the different renewable energies mentioned above. The results provided by the software used, *REopt*®, are relevant and allow to provide a number of scenarios giving a resilience capability, which is introduced as an input, while, at the same time, provides financial insights from a business perspective. By installing photovoltaic panels, Li-ion batteries and diesel generators, the microgrid could save approximately \$440,191 over a 20-years life cycle of the facility.

Acknowledgements

The authors acknowledge the financial support provided by the Cabildo de Tenerife (through the Agustín de Betancourt Program) to conduct activities for the research project titled “Huertos comunitarios autosuficientes en zonas áridas: Reducción del coste normalizado de la energía y eliminación de la dependencia

hídrica a través de energías renovables”. The authors confirm that this work has not spread any type of information that could undermine the knowledge protection generated in the aforementioned project.

Appendix 1: Results Comparison

See Table 3.

Table 3 Comparison between the business as usual approach and the optimal case according to June 21st with a shutdown at 2 a.m. for 16 h

	Business as usual	Optimal case	Difference
<i>System size, energy production and system cost</i>			
PV size	0 kW	1134 kW	1134 kW
Annualized PV energy production	0 kWh	1,836,030 kWh	1,836,030 kWh
Battery power	0 kW	114 kW	114 kW
Battery capacity	0 kWh	276 kWh	276 kWh
DG system cost (Net CAPEX + O&M)	\$0	\$1,634,873	\$1,634,873
Energy supplied from grid in year 1	4,894,390 kWh	3,115,318 kWh	1,779,072 kWh
<i>Utility cost (year 1)—before tax</i>			
Utility energy cost	\$377,442	\$226,796	\$150,646
Utility demand cost	\$248,894	\$168,147	\$80,747
Utility fixed cost	\$0	\$0	\$0
Utility minimum cost adder	\$0	\$0	\$0
<i>Life cycle utility cost—after tax</i>			
Utility energy cost	\$3,376,765	\$2,029,021	\$1,347,744
Utility demand cost	\$2,226,718	\$1,504,321	\$722,396
Utility fixed cost	\$0	\$0	\$0
Utility minimum cost adder	\$0	\$0	\$0
<i>Total system and life cycle utility cost—after tax</i>			
Life cycle energy cost (LCC)	\$5,603,483	\$5,168,215	\$435,268
Net present value (NPV)	\$0	\$435,268	\$435,628

Source Own elaboration

Appendix 2: Summary of Model Inputs

See Table 4.

Table 4 Summary of the model inputs

Site and utility	
Site location	Palmdale, CA
Latitude	34.579434
Longitude	−118.116461
Land available (acres)	34.17
Roofspace available (sq ft)	320,000

Load profile	Simulated
Type of building	Hospital
Annual energy consumption (kWh)	4,900,000
URDB rate	Southern California Edison Co time-of-use—general service—large: TOU-8 CPP (2–50 kV) last updated 2016-02-10
Financial parameters	
Analysis period (years)	20
Host discount rate, nominal (%)	8.1%
Host effective tax rate (%)	26%
Electricity cost escalation rate, nominal (%)	2.6%
O&M cost escalation rate (%)	2.5%
Solar photovoltaic system	
System capital cost (\$/kW)	\$2,000
O&M cost (\$/kW per year)	\$16
Minimum size desired (kW DC)	0
Maximum size desired (kW DC)	Unlimited
Module type	Standard
Array type	Rooftop, fixed
Array azimuth (deg)	180
Array tilt (deg)	10.0
DC to AC size ratio	1.1
System losses (%)	14%
Net metering system size limit (kW)	0
Federal percentage-based incentive (%)	30%
Federal maximum incentive (\$)	Unlimited
Federal rebate (\$/kW)	\$0
Federal maximum rebate (\$)	Unlimited
State percentage-based incentive (%)	0%
State maximum incentive (\$)	Unlimited
State rebate (\$/kW)	\$0
State maximum rebate (\$)	Unlimited
Utility percentage-based incentive (%)	0%
Utility maximum incentive (\$)	Unlimited
Utility rebate (\$/kW)	\$0
Utility maximum rebate (\$)	Unlimited
Production incentive (\$/kWh)	\$0
Incentive duration (years)	1
Maximum incentive (\$)	Unlimited
System size limit (kW)	Unlimited
MACRS schedule	5

Energy storage system	
Energy capacity cost (\$/kWh)	\$500
Power capacity cost (\$/kW)	\$1000
Energy capacity replacement cost (\$/kWh)	\$230
Energy capacity replacement year	10
Power capacity replacement cost (\$/kW)	\$460
Power capacity replacement year	10
Minimum energy capacity (kWh)	0
Maximum energy capacity (kWh)	Unlimited
Minimum power capacity (kW)	0
Maximum power capacity (kW)	Unlimited
Rectifier efficiency (%)	96%
Round trip efficiency (%)	97.5%
Inverter efficiency (%)	96%
Minimum state of charge (%)	20%
Initial state of charge (%)	50%
Allow grid to charge battery	Yes
Total percentage-based incentive (%)	0%
Total rebate (\$/kW)	\$0
MACRS schedule	7
Resilience	
Critical load factor	50%

Source Own elaboration

Appendix 3: Graphical Outputs

See Figs. 2, 3, 4, 5, 6, 7, 8, and 9.

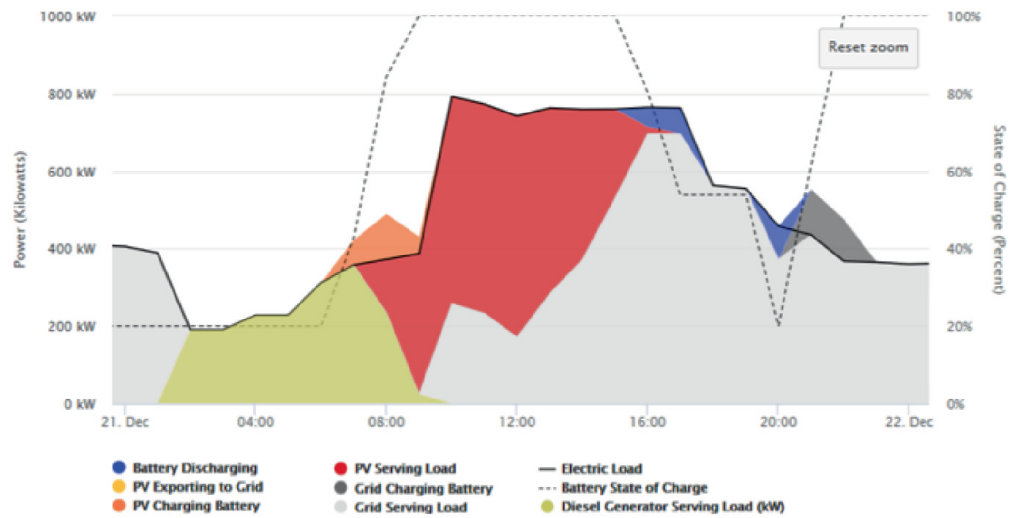


Fig. 2 Energy dispatch on December 21st with a shutdown at 2 a.m. for 8 h.
Source Own elaboration

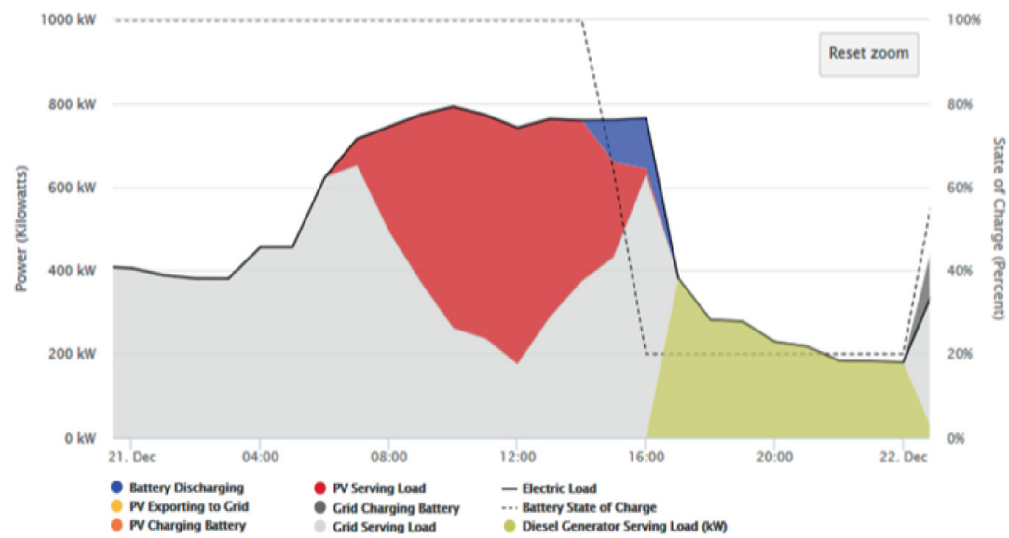


Fig. 3 Energy dispatch on December 21st with a shutdown at 5 p.m. for 8 h.
Source Own elaboration

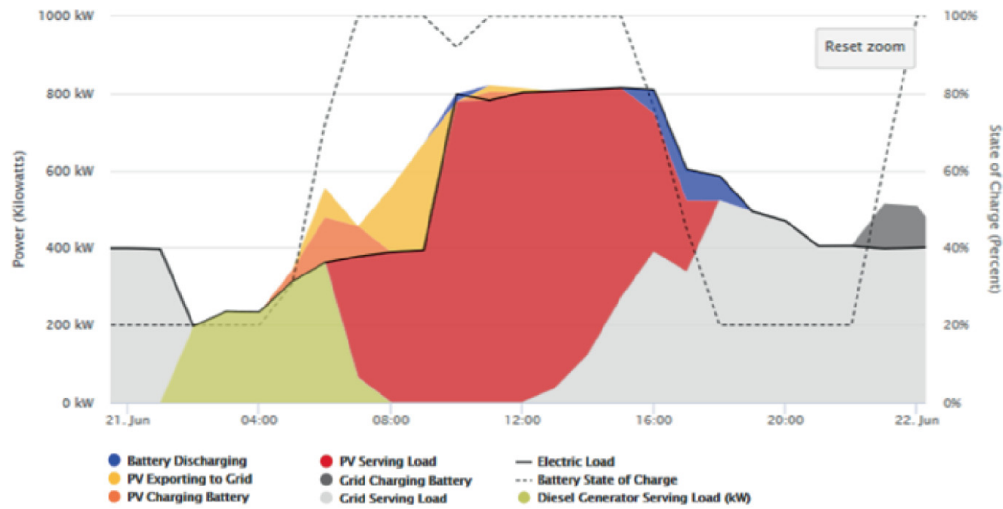


Fig. 4 Energy dispatch on June 21st with a shutdown at 2 a.m. for 8 h.
Source Own elaboration

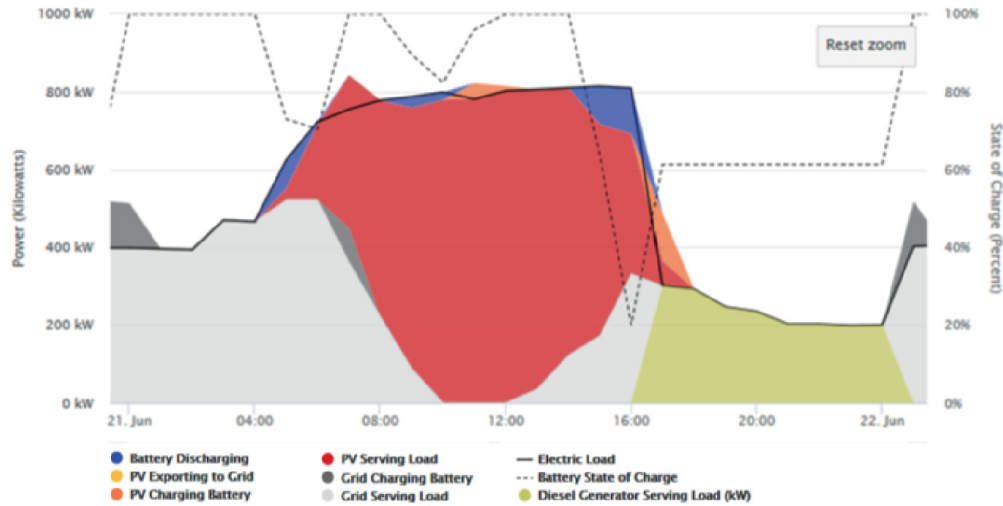


Fig. 5 Energy dispatch on June 21st with a shutdown at 5 p.m. for 8 h.
Source Own elaboration

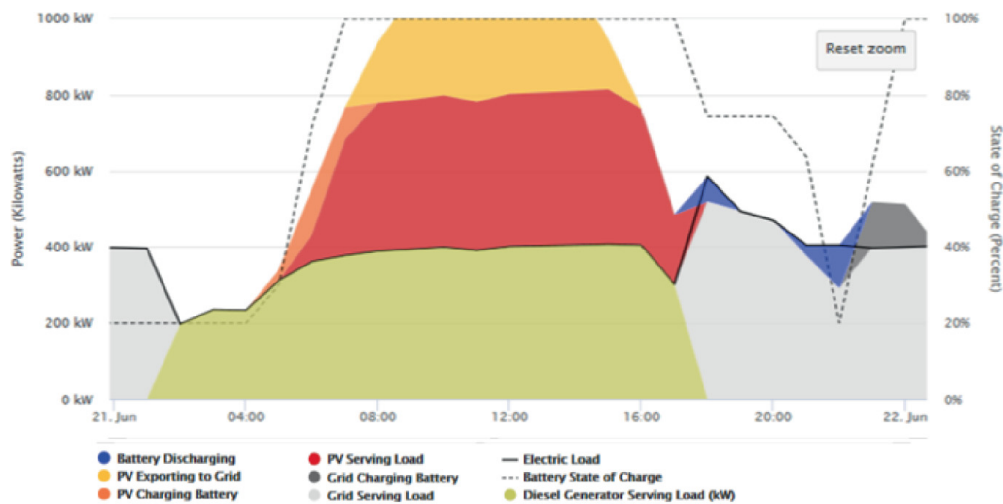


Fig. 6 Energy dispatch on June 21st with a shutdown at 2 a.m. for 16 h.
Source: Own elaboration

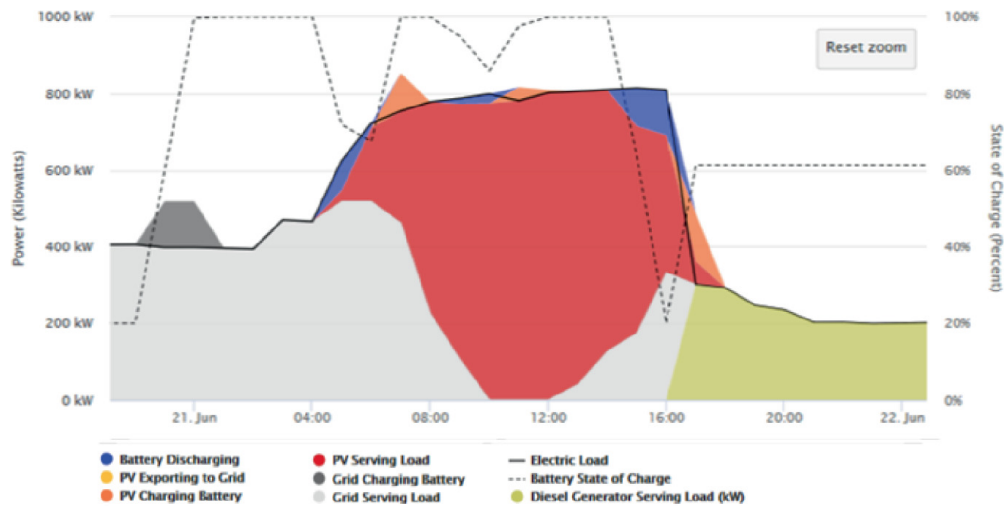


Fig. 7 Energy dispatch on June 21st with a shutdown at 5 p.m. for 16 h.
Source: Own elaboration

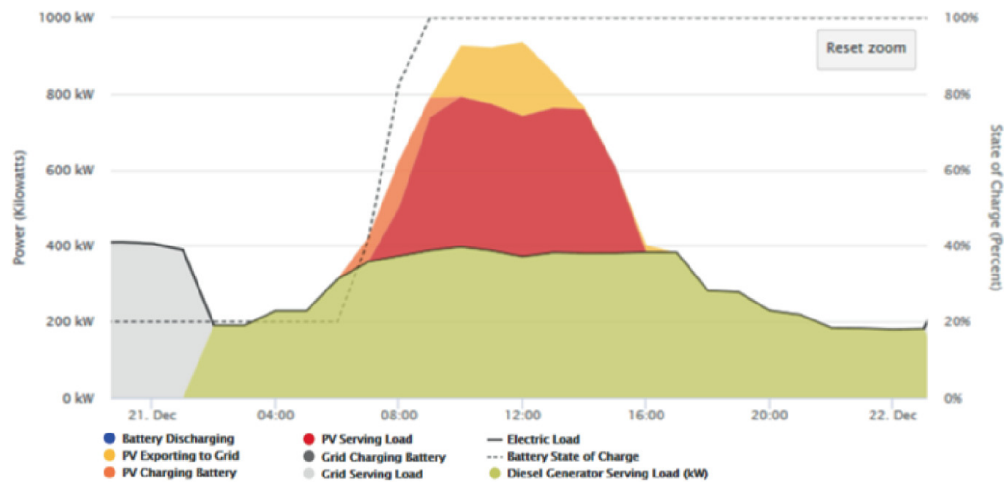


Fig. 8 Energy dispatch on December 21st with a shutdown at 2 a.m. for 24 h.
Source: Own elaboration

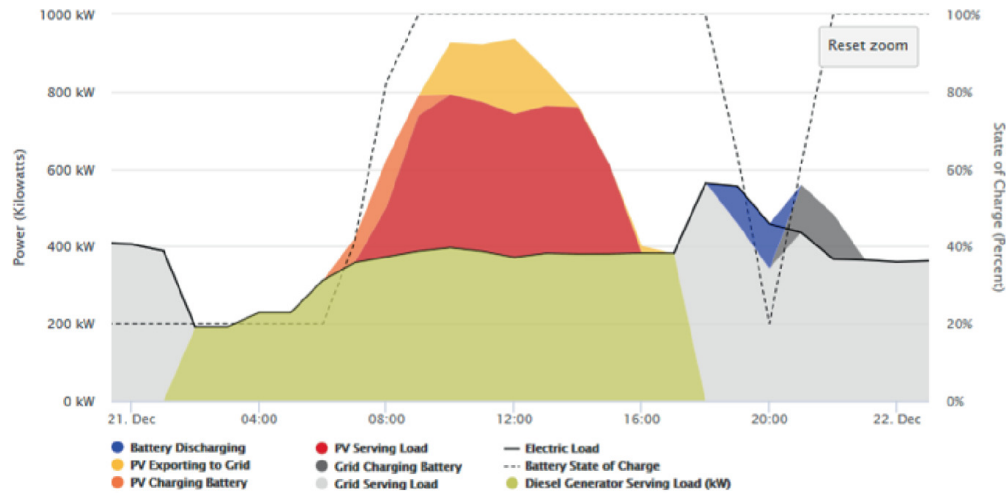


Fig. 9 Energy dispatch on December 21st with a shutdown at 2 a.m. for 16 h.
Source Own elaboration

Appendix 4: Supplementary Material: Output Data from Simulations

See Tables 5, 6, 7, 8, 9, 10, 11, and 12.

Table 5 Values from REopt® simulation Fig. 2

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/12/2017 23:00	409.7	409.7	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/12/2017 0:00	405.6	405.6	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/12/2017 1:00	388.6	388.6	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/12/2017 2:00	190.4	0.0	0.0	0.0	0.0	0.0	0.0	20.0	190.4
21/12/2017 3:00	190.2	0.0	0.0	0.0	0.0	0.0	0.0	20.0	190.2
21/12/2017 4:00	228.1	0.0	0.0	0.0	0.0	0.0	0.0	20.0	228.1
21/12/2017 5:00	228.1	0.0	0.0	0.0	0.0	0.0	0.0	20.0	228.1
21/12/2017 6:00	311.4	0.0	0.0	0.0	0.0	0.0	0.0	20.0	311.4
21/12/2017 7:00	357.4	0.0	0.0	0.0	64.4	0.0	0.0	40.0	357.4
21/12/2017 8:00	372.3	0.0	137.8	0.0	117.0	0.0	0.0	80.0	234.5
21/12/2017 9:00	386.8	0.0	362.3	0.0	44.0	0.0	0.0	100.0	24.5
21/12/2017	792.4	257.7	534.7	0.0	0.0	0.0	0.0	100.0	0.0

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
10:00									
21/12/2017 11:00	772.7	233.2	539.5	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 12:00	742.0	171.0	570.9	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 13:00	763.0	283.8	479.2	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 14:00	759.6	371.2	388.4	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 15:00	760.1	530.4	229.7	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 16:00	764.4	695.9	19.0	49.5	0.0	0.0	0.0	80.0	0.0
21/12/2017 17:00	763.0	695.9	0.0	67.1	0.0	0.0	0.0	50.0	0.0
21/12/2017 18:00	563.2	563.2	0.0	0.0	0.0	0.0	0.0	50.0	0.0
21/12/2017 19:00	555.2	555.2	0.0	0.0	0.0	0.0	0.0	50.0	0.0
21/12/2017 20:00	457.9	372.0	0.0	85.9	0.0	0.0	0.0	20.0	0.0
21/12/2017 21:00	435.6	435.6	0.0	0.0	0.0	117.0	0.0	60.0	0.0
21/12/2017 22:00	367.4	367.4	0.0	0.0	0.0	108.4	0.0	100.0	0.0
21/12/2017 23:00	364.9	364.9	0.0	0.0	0.0	0.0	0.0	100.0	0.0
22/12/2017 0:00	359.5	359.5	0.0	0.0	0.0	0.0	0.0	100.0	0.0

Energy dispatch on December 21st with a shutdown at 2 a.m. for 8 h. *Source* Own elaboration

Table 6 Values from REopt® simulation Fig. 3

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/12/2017 23:00	409.7	409.7	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 0:00	405.6	405.6	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 1:00	388.6	388.6	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 2:00	380.8	380.8	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 3:00	380.5	380.5	0.0	0.0	0.0	0.0	0.0	100.0	0.0

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
21/12/2017 4:00	456.1	456.1	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 5:00	456.3	456.3	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 6:00	622.8	622.8	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 7:00	714.9	650.9	64.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 8:00	744.6	491.3	253.3	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 9:00	773.6	369.5	404.1	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 10:00	792.4	260.7	531.7	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 11:00	772.7	236.2	536.5	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 12:00	742.0	174.2	567.7	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 13:00	763.0	286.5	476.5	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 14:00	759.6	373.4	386.2	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 15:00	760.1	431.6	228.4	100.0	0.0	0.0	0.0	60.0	0.0
21/12/2017 16:00	764.4	626.3	18.9	119.3	0.0	0.0	0.0	20.0	0.0
21/12/2017 17:00	381.5	0.0	0.0	0.0	0.0	0.0	0.0	20.0	381.5
21/12/2017 18:00	281.6	0.0	0.0	0.0	0.0	0.0	0.0	20.0	281.6
21/12/2017 19:00	277.6	0.0	0.0	0.0	0.0	0.0	0.0	20.0	277.6
21/12/2017 20:00	228.9	0.0	0.0	0.0	0.0	0.0	0.0	20.0	228.9
21/12/2017 21:00	217.8	0.0	0.0	0.0	0.0	0.0	0.0	20.0	217.8
21/12/2017 22:00	183.7	0.0	0.0	0.0	0.0	0.0	0.0	20.0	183.7
21/12/2017 23:00	182.5	0.0	0.0	0.0	0.0	0.0	0.0	20.0	182.5
22/12/2017 0:00	179.7	0.0	0.0	0.0	0.0	0.0	0.0	20.0	179.7

Energy dispatch on December 21st with a shutdown at 5 p.m. for 8 h. *Source* Own elaboration

Table 7 Values from REopt® simulation Fig. 4

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/06/2017 23:00	398.4	398.4	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 0:00	398.5	398.5	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 1:00	396.3	396.3	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 2:00	196.8	0.0	0.0	0.0	0.0	0.0	0.0	20.0	196.8
21/06/2017 3:00	234.9	0.0	0.0	0.0	0.0	0.0	0.0	20.0	234.9
21/06/2017 4:00	233.1	0.0	0.0	0.0	0.0	0.0	0.0	20.0	233.1
21/06/2017 5:00	312.1	0.0	0.0	0.0	30.0	0.0	0.0	30.0	312.1
21/06/2017 6:00	361.4	0.0	0.0	0.0	117.1	0.0	76.5	70.0	361.4
21/06/2017 7:00	377.4	0.0	313.8	0.0	78.5	0.0	0.0	100.0	63.6
21/06/2017 8:00	389.0	0.0	389.0	0.0	0.0	0.0	165.9	100.0	0.0
21/06/2017 9:00	393.5	0.0	393.5	0.0	0.0	0.0	276.6	100.0	0.0
21/06/2017 10:00	798.6	0.0	778.2	20.4	0.0	0.0	0.0	90.0	0.0
21/06/2017 11:00	781.3	0.0	781.3	0.0	22.7	0.0	16.6	100.0	0.0
21/06/2017 12:00	802.4	0.0	802.4	0.0	0.0	0.0	10.8	100.0	0.0
21/06/2017 13:00	806.0	36.2	769.8	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 14:00	809.9	123.2	686.6	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 15:00	814.0	270.1	543.9	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 16:00	809.1	388.8	360.6	59.8	0.0	0.0	0.0	80.0	0.0
21/06/2017 17:00	602.7	337.3	185.3	80.0	0.0	0.0	0.0	40.0	0.0
21/06/2017 18:00	585.2	522.3	0.0	63.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 19:00	493.7	493.7	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 20:00	469.7	469.7	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 21:00	404.4	404.4	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 22:00	404.8	404.8	0.0	0.0	0.0	0.0	0.0	20.0	0.0

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
21/06/2017 23:00	397.6	397.6	0.0	0.0	0.0	117.1	0.0	60.0	0.0
22/06/2017 0:00	400.1	400.1	0.0	0.0	0.0	108.6	0.0	100.0	0.0

Energy dispatch on June 21st with a shutdown at 2 a.m. for 8 h. *Source Own elaboration*

Table 8 Values from REopt® simulation Fig. 5

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/06/2017 23:00	398.4	398.4	0.0	0.0	0.0	122.8	0.0	60.0	0.0
21/06/2017 0:00	398.5	398.5	0.0	0.0	0.0	114.8	0.0	100.0	0.0
21/06/2017 1:00	396.3	396.3	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 2:00	393.7	393.7	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 3:00	469.8	469.8	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 4:00	466.1	466.1	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 5:00	624.2	522.0	30.1	72.1	0.0	0.0	0.0	70.0	0.0
21/06/2017 6:00	722.7	522.0	193.9	6.8	0.0	0.0	0.0	70.0	0.0
21/06/2017 7:00	754.8	361.9	392.9	0.0	0.0	87.8	0.0	100.0	0.0
21/06/2017 8:00	778.0	222.4	555.7	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 9:00	787.0	88.3	671.0	27.7	0.0	0.0	0.0	90.0	0.0
21/06/2017 10:00	798.6	0.0	779.3	19.3	0.0	0.0	0.0	80.0	0.0
21/06/2017 11:00	781.3	0.0	781.3	0.0	40.4	0.0	0.0	100.0	0.0
21/06/2017 12:00	802.4	0.0	802.4	0.0	11.9	0.0	0.0	100.0	0.0
21/06/2017 13:00	806.0	35.1	770.8	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 14:00	809.9	122.3	687.6	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 15:00	814.0	172.3	544.6	97.1	0.0	0.0	0.0	60.0	0.0
21/06/2017	809.1	331.7	361.1	116.4	0.0	0.0	0.0	20.0	0.0

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
16:00									
21/06/2017 17:00	301.3	0.0	62.8	0.0	122.8	0.0	0.0	60.0	301.3
21/06/2017 18:00	292.6	0.0	0.0	0.0	0.0	0.0	0.0	60.0	292.6
21/06/2017 19:00	246.8	0.0	0.0	0.0	0.0	0.0	0.0	60.0	246.8
21/06/2017 20:00	234.8	0.0	0.0	0.0	0.0	0.0	0.0	60.0	234.8
21/06/2017 21:00	202.2	0.0	0.0	0.0	0.0	0.0	0.0	60.0	202.2
21/06/2017 22:00	202.4	0.0	0.0	0.0	0.0	0.0	0.0	60.0	202.4
21/06/2017 23:00	198.8	0.0	0.0	0.0	0.0	0.0	0.0	60.0	198.8
22/06/2017 0:00	200.1	0.0	0.0	0.0	0.0	0.0	0.0	60.0	200.1

Energy dispatch on June 21st with a shutdown at 5 p.m. for 8 h. *Source* Own elaboration

Table 9 Values from REopt® simulation Fig. 6

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/06/2017 23:00	398.4	398.4	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 0:00	398.5	398.5	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 1:00	396.3	396.3	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/06/2017 2:00	196.8	0.0	0.0	0.0	0.0	0.0	0.0	20.0	196.8
21/06/2017 3:00	234.9	0.0	0.0	0.0	0.0	0.0	0.0	20.0	234.9
21/06/2017 4:00	233.1	0.0	0.0	0.0	0.0	0.0	0.0	20.0	233.1
21/06/2017 5:00	312.1	0.0	0.0	0.0	29.7	0.0	0.0	30.0	312.1
21/06/2017 6:00	361.4	0.0	71.4	0.0	120.5	0.0	0.0	70.0	361.4
21/06/2017 7:00	377.4	0.0	306.0	0.0	82.7	0.0	0.0	100.0	377.4
21/06/2017 8:00	389.0	0.0	389.0	0.0	0.0	0.0	160.8	100.0	389.0
21/06/2017 9:00	393.5	0.0	393.5	0.0	0.0	0.0	270.4	100.0	393.5

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
21/06/2017 10:00	399.3	0.0	399.3	0.0	0.0	0.0	371.8	100.0	399.3
21/06/2017 11:00	390.6	0.0	390.6	0.0	0.0	0.0	422.4	100.0	390.6
21/06/2017 12:00	401.2	0.0	401.2	0.0	0.0	0.0	404.6	100.0	401.2
21/06/2017 13:00	403.0	0.0	403.0	0.0	0.0	0.0	359.8	100.0	403.0
21/06/2017 14:00	404.9	0.0	404.9	0.0	0.0	0.0	275.5	100.0	404.9
21/06/2017 15:00	407.0	0.0	407.0	0.0	0.0	0.0	131.9	100.0	407.0
21/06/2017 16:00	404.6	0.0	357.3	0.0	0.0	0.0	0.0	100.0	404.6
21/06/2017 17:00	301.3	0.0	183.6	0.0	0.0	0.0	0.0	100.0	301.3
21/06/2017 18:00	585.2	518.3	0.0	67.0	0.0	0.0	0.0	70.0	0.0
21/06/2017 19:00	493.7	493.7	0.0	0.0	0.0	0.0	0.0	70.0	0.0
21/06/2017 20:00	469.7	469.7	0.0	0.0	0.0	0.0	0.0	70.0	0.0
21/06/2017 21:00	404.4	376.3	0.0	28.1	0.0	0.0	0.0	60.0	0.0
21/06/2017 22:00	404.8	290.6	0.0	114.2	0.0	0.0	0.0	20.0	0.0
21/06/2017 23:00	397.6	397.6	0.0	0.0	0.0	120.5	0.0	60.0	0.0
22/06/2017 0:00	400.1	400.1	0.0	0.0	0.0	112.4	0.0	100.0	0.0

Energy dispatch on June 21st with a shutdown at 2 a.m. for 16 h. *Source* Own elaboration

Table 10 Values from REopt® simulation Fig. 7

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/06/2017 23:00	398.4	398.4	0.0	0.0	0.0	119.8	0.0	60.0	0.0
21/06/2017 0:00	398.5	398.5	0.0	0.0	0.0	119.8	0.0	100.0	0.0
21/06/2017 1:00	396.3	396.3	0.0	0.0	0.0	1.0	0.0	100.0	0.0
21/06/2017 2:00	393.7	393.7	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017	469.8	469.8	0.0	0.0	0.0	0.0	0.0	100.0	0.0

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
3:00									
21/06/2017 4:00	466.1	466.1	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 5:00	624.2	518.3	29.9	76.0	0.0	0.0	0.0	70.0	0.0
21/06/2017 6:00	722.7	518.3	192.6	11.8	0.0	0.0	0.0	70.0	0.0
21/06/2017 7:00	754.8	462.2	292.6	0.0	97.8	0.0	0.0	100.0	0.0
21/06/2017 8:00	778.0	225.8	552.2	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 9:00	787.0	106.7	666.7	13.6	0.0	0.0	0.0	90.0	0.0
21/06/2017 10:00	798.6	0.0	774.4	24.2	0.0	0.0	0.0	90.0	0.0
21/06/2017 11:00	781.3	0.0	781.3	0.0	35.2	0.0	0.0	100.0	0.0
21/06/2017 12:00	802.4	0.0	802.4	0.0	6.8	0.0	0.0	100.0	0.0
21/06/2017 13:00	806.0	40.0	766.0	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 14:00	809.9	126.6	683.2	0.0	0.0	0.0	0.0	100.0	0.0
21/06/2017 15:00	814.0	174.4	541.2	98.5	0.0	0.0	0.0	60.0	0.0
21/06/2017 16:00	809.1	332.7	358.8	117.7	0.0	0.0	0.0	20.0	0.0
21/06/2017 17:00	301.3	0.0	60.3	0.0	124.1	0.0	0.0	60.0	301.3
21/06/2017 18:00	292.6	0.0	0.0	0.0	0.0	0.0	0.0	60.0	292.6
21/06/2017 19:00	246.8	0.0	0.0	0.0	0.0	0.0	0.0	60.0	246.8
21/06/2017 20:00	234.8	0.0	0.0	0.0	0.0	0.0	0.0	60.0	234.8
21/06/2017 21:00	202.2	0.0	0.0	0.0	0.0	0.0	0.0	60.0	202.2
21/06/2017 22:00	202.4	0.0	0.0	0.0	0.0	0.0	0.0	60.0	202.4
21/06/2017 23:00	198.8	0.0	0.0	0.0	0.0	0.0	0.0	60.0	198.8
22/06/2017 0:00	200.1	0.0	0.0	0.0	0.0	0.0	0.0	60.0	200.1

Energy dispatch on June 21st with a shutdown at 5 p.m. for 16 h. *Source* Own elaboration

Table 11 Values from REopt® simulation Fig. 8

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
21/12/2017 23:00	182.5	0.0	0.0	0.0	0.0	0.0	0.0	100.0	182.5
22/12/2017 0:00	179.7	0.0	0.0	0.0	0.0	0.0	0.0	100.0	179.7

Energy dispatch on December 21st with a shutdown at 2 a.m. for 24 h. *Source* Own elaboration

Table 12 Values from REopt® simulation Fig. 9

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
20/12/2017 23:00	409.7	409.7	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/12/2017 0:00	405.6	405.6	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/12/2017 1:00	388.6	388.6	0.0	0.0	0.0	0.0	0.0	20.0	0.0
21/12/2017 2:00	190.4	0.0	0.0	0.0	0.0	0.0	0.0	20.0	190.4
21/12/2017 3:00	190.2	0.0	0.0	0.0	0.0	0.0	0.0	20.0	190.2
21/12/2017 4:00	228.1	0.0	0.0	0.0	0.0	0.0	0.0	20.0	228.1
21/12/2017 5:00	228.1	0.0	0.0	0.0	0.0	0.0	0.0	20.0	228.1
21/12/2017 6:00	311.4	0.0	0.0	0.0	0.0	0.0	0.0	20.0	311.4
21/12/2017 7:00	357.4	0.0	0.0	0.0	63.8	0.0	0.0	40.0	357.4
21/12/2017 8:00	372.3	0.0	129.2	0.0	123.5	0.0	0.0	80.0	372.3
21/12/2017 9:00	386.8	0.0	351.1	0.0	51.9	0.0	0.0	100.0	386.8
21/12/2017 10:00	396.2	0.0	396.2	0.0	0.0	0.0	134.2	100.0	396.2
21/12/2017 11:00	386.4	0.0	386.4	0.0	0.0	0.0	148.8	100.0	386.4
21/12/2017 12:00	371.0	0.0	371.0	0.0	0.0	0.0	195.3	100.0	371.0
21/12/2017 13:00	381.5	0.0	381.5	0.0	0.0	0.0	93.8	100.0	381.5
21/12/2017 14:00	379.8	0.0	379.8	0.0	0.0	0.0	5.4	100.0	379.8
21/12/2017 15:00	380.0	0.0	227.8	0.0	0.0	0.0	0.0	100.0	380.0
21/12/2017	382.2	0.0	0.0	0.0	0.0	0.0	18.9	100.0	382.2

Time stamp	Electric load (kW)	Grid serving load (kW)	PV serving load (kW)	Battery discharging (kW)	PV charging battery (kW)	Grid charging battery (kW)	PV exporting to grid (kW)	Battery SoC (%)	Diesel generator serving load (kW)
16:00									
21/12/2017 17:00	381.5	0.0	0.0	0.0	0.0	0.0	0.0	100.0	381.5
21/12/2017 18:00	563.2	563.2	0.0	0.0	0.0	0.0	0.0	100.0	0.0
21/12/2017 19:00	555.2	457.3	0.0	97.9	0.0	0.0	0.0	60.0	0.0
21/12/2017 20:00	457.9	340.8	0.0	117.1	0.0	0.0	0.0	20.0	0.0
21/12/2017 21:00	435.6	435.6	0.0	0.0	0.0	123.5	0.0	60.0	0.0
21/12/2017 22:00	367.4	367.4	0.0	0.0	0.0	115.7	0.0	100.0	0.0
21/12/2017 23:00	364.9	364.9	0.0	0.0	0.0	0.0	0.0	100.0	0.0
22/12/2017 0:00	359.5	359.5	0.0	0.0	0.0	0.0	0.0	100.0	0.0

Energy dispatch on December 21st with a shutdown at 2 a.m. for 16 h. *Source* Own elaboration

References

1. AMERESCO (2017) The rise of clean energy microgrids. Why microgrids make sense for hospitals, higher education, military and government, and businesses. Why choose a clean energy microgrid? And clean energy microgrids for hospitals. E-Publishing Inc, pp 1-6
2. Anderson K, Laws DN, Marr S, Lisell L, Jimenez T, Case T, Li X, Lohmann D, Cutler D (2017) Quantifying and monetizing renewable energy resiliency. National Renewable Energy Laboratory, Denver. <https://www.nrel.gov/docs/fy18osti/71143.pdf>. Accessed 9 April 2019
3. NREL/JA-7A40-69034 (2017) Journal of energy management. In: Anderson K, DiOrio N, Cutler D, Butt B (eds) Increasing resiliency through renewable energy microgrids, pp 22-38
4. Shouman ER, El-Shenawy ET, Khattab NM (2016) Market financial analysis and cost performance for photovoltaic technology through international and national perspective with case study for Egypt. Energy 57:540-549. <https://doi.org/10.1016/j.rser.2015.12.074> [Crossref]
5. Ramadhan M, Naseeb A (2011) The cost benefit analysis of implementing photovoltaic solar system in the state of Kuwait. Energy 36:1272-1276. <https://doi.org/10.1016/j.renene.2010.10.004> [Crossref]
6. O'Mahoney A, Thorne F, Denny E (2019) A cost-benefit analysis of generating electricity from biomass. Energy 57:347-354. <https://doi.org/10.1016/j.enpol.2013.02.005> [Crossref]
7. Tudisca S, Di Trapani AM, Sgroi F, Testa R, Squatrito R (2013) Economic analysis of PV systems on buildings in Sicilian farms. Energy 28:691-701. <https://doi.org/10.1016/j.rser.2013.08.035> [Crossref]
8. Feng W, Jin M, Liu X, Bao Y, Marnay C, Yao C, Yu J (2018) A review of microgrid development in the United: a decade of progress on policies demonstrations controls and software tools. Energy 228:1656-1668. <https://doi.org/10.1016/j.apenergy.2018.06.096> [Crossref]

9. Mengelkamp E, Gärttner J, Rock K, Kessel S, Orsini L, Weinhardt C (2018) Designing microgrid energy markets: a case study—the Brooklyn microgrid. *Energy* 210:870–880. <https://doi.org/10.1016/j.apenergy.2017.06.054> [Crossref]
10. Bartolucci L, Cordiner S, Mulone V, Rocco V, Rossi JL (2018) Hybrid renewable energy systems for renewable integration in microgrids: influence of sizing on performance. *Energy* 152:744–758. <https://doi.org/10.1016/j.energy.2018.03.165> [Crossref]
11. Hirsch A, Parag Y, Guerrero J (2018) Microgrids: a review of technologies key drivers and outstanding issues. *Energy* 90:402–411. <https://doi.org/10.1016/j.rser.2018.03.040> [Crossref]
12. Cattaneo A, Madathil SC, Backhaus S (2018) Integration of optimal operational dispatch and controller determined dynamics for microgrid survivability. *Energy* 230:1685–1696. <https://doi.org/10.1016/j.apenergy.2018.08.127> [Crossref]
13. Hussain A, Bui V-H, Kim H-M (2019) Microgrids as a resilience resource and strategies used by microgrids for enhancing resilience. *Energy* 240:56–72. <https://doi.org/10.1016/j.apenergy.2019.02.055> [Crossref]
14. Rosales-Asensio E, Simón-Martín M, Borge-Diez D, Blanes-Peiró JJ, Colmenar-Santos A (2019) Microgrids with energy storage systems as a means to increase power resilience: an application to office buildings. *Energy* 172:1005–1015. <https://doi.org/10.1016/j.energy.2019.02.043> [Crossref]
15. Zhou Y, Panteli M, Moreno R, Mancarrella P (2018) System-level assessment of reliability and resilience provision from microgrids. *Energy* 230:374–392. <https://doi.org/10.1016/j.apenergy.2018.08.054> [Crossref]
16. Jufri FH, Widiputra V, Jung J (2019) State-of-the-art review on power grid resilience to extreme weather events: definitions, frameworks, quantitative assessment methodologies, and enhancement strategies. *Energy* 239:1049–1065. <https://doi.org/10.1016/j.apenergy.2019.02.017> [Crossref]
17. Arghandeh R, Meier AV, Mehrmanesh L, Mili L (2016) On the definition of cyber-physical resilience in power systems. *Energy* 58:1060–1069. <https://doi.org/10.1016/j.rser.2015.12.193> [Crossref]
18. Prehoda EW, Schelly C, Pearce MJ (2017) U.S. strategic solar photovoltaic-powered microgrid deployment for enhanced national security. *Energy* 78:167–175. <https://doi.org/10.1016/j.rser.2017.04.094> [Crossref]
19. NREL (2018) Renewable energy integration and optimization. National Renewable Energy Laboratory, Denver. <https://reopt.nrel.gov/tool>
20. NREL (2017) Renewable energy optimization (REopt). National Renewable Energy Laboratory, Denver. <https://reopt.nrel.gov/tool/REopt%20Lite%20Web%20Tool%20User%20Manual.pdf>. Accessed 7 May 2018
21. Tozzi P, Ho JJ (2017) A comparative analysis of renewable energy simulation tools: performance simulation model versus system optimization. *Renew Sustain Energy Rev* 80:390–398. <https://doi.org/10.1016/j.rser.2017.05.153> [Crossref]
22. Palmdale Regional Medical Center. https://en.wikipedia.org/wiki/Palmdale_Regional_Medical_Center. Accessed 10 April 2019
23. Net metering Program Overview. <http://programs.dsireusa.org/system/program/detail/276>. Accessed 12 May 2019
24. COINNEWS MEDIA GROUP LLC. Historical inflation rates: 1914–2018. <http://www.usinflationcalculator.com/inflation/historical-inflation-rates/>. Accessed 15 May 2019

25. Emergency power back-up for hospitals: an overview. <http://www.primepower.com/blog/emergency-power-back-up-for-hospitals-an-overview/>. Accessed 16 May 2019
26. Hecla GREENS CREEK. General plan of operations. Srk consulting, Alaska
27. Laws ND, Anderson K, DiOrio NA, Li X, McLaren J (2018) Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings. *Renew Energy* 127:896-909
[Crossref]
28. Centolella P, Farber-DeAnda M, Greening AL, Kim T (2018) Estimates of the value of uninterrupted service for the mid-west independent system operator, p 4
29. Bustos C, Watts D (2016) Novel methodology for microgrids in isolated communities: electricity cost-coverage trade-off with 3 stage technology mix, dispatch and configuration optimizations. *Appl Energy* 195:204-221
[Crossref]
30. Sullivan MJ, Schellenberg J, Blundell M (2015) Updated value of service reliability estimates for electric utility customers in the United States. In: Technical report, Lawrence Berkeley National Laboratory
31. U.S.-Canada power system outage task force. The Blackout in the United States and Canada, August 14, 2003. Causes and recommendations, p 116
32. Patsios C, Wu B, Chatzinikolaou E, Rogers DJ, Wade N, Brandon NP, Taylor P (2016) An integrated approach for the analysis and control of grid connected energy storage systems. *Energy* 5:48-61. <https://doi.org/10.1016/j.est.2015.11.011>
[Crossref]

Resilience Improvement in PostCOVID-19 Medical Centers

Josep Hervás-Zaragoza¹, Antonio Colmenar-Santos¹,
Enrique Rosales-Asensio²  and Lucía Colmenar-Fernández³

- (1) Departamento de Ingeniería Eléctrica, Electrónica, Control, Telemática y Química Aplicada a la Ingeniería, UNED, Juan del Rosal, 12, Ciudad Universitaria, 28040 Madrid, Spain
- (2) Departamento de Ingeniería Eléctrica, Escuela de Ingenierías Industriales y Civiles, ULPGC, Campus de Tafira s/n, 35017 Canary Islands, Spain
- (3) Facultad de Medicina, Universidad de Alcalá de Henares, Madrid, Spain

 **Enrique Rosales-Asensio**
Email: enrique.rosales@ulpgc.es

Abstract

The high number of natural disasters in recent years, combined with the emergence of COVID-19 and the pressure it has exerted on healthcare services, has led to the need to guarantee the power supply to critical infrastructures. In this context, ensuring critical loads of hospital has become a mandatory task. Thus, the aim of the work presented here is to improve the energy resilience of

a hospital through the installation of a microgrid consisting of a photovoltaic system working together with a diesel generator in the energy resilience scenario. In the first scenario, it has been evaluated how a microgrid is economically viable for the case where there is no grid outage. In the second scenario, the microgrid has been optimised taking into account both the economic profitability and the ability to withstand a 24-h outage in the month of lowest radiation. The results obtained have shown that the microgrid consisting of a PV system, an energy storage system and a backup diesel generator was able to withstand the 24-h outage at any time of the year, providing the hospital with a net gain of 24 h in terms of energy resilience compared to the business as usual (BaU).

Keywords Microgrids - Energy resilience - Grid outages - Hospitals

Nomenclatures

BESS Battery energy storage system

BaU Business as usual

LCC Life cycle cost

LID Light induced degradation

MILP Mixed integer linear programming

N Duration of years

NPV Net present value

NREL National renewable energy laboratory

RE Renewable energy

SoC State of charge

1 Introduction

The term energy resilience is based on preventing power outages and restoring power as quickly as possible when an outage occurs, while mitigating the consequences of the outage [1]. In recent years, a series of events have led to energy resilience and the improvement of this parameter in critical infrastructures becoming highly relevant in both the governmental and research spheres. As evidence of this, many decision- and policy-makers are already integrating resilience considerations into their planning priorities, as exemplified by the various guides [2–6] that have been developed for stakeholders in resilience planning and enhancement.

On the one hand, the number of natural disasters and their economic effects are increasing. In global terms, the United States has suffered a total of 323 natural disasters since 1980 with economic costs reaching or exceeding \$1 billion and with cumulative costs now exceeding \$2.2 trillion, the latest statistics [7] indicate that in 2021 there were a total of 20 natural disasters with economic effects reaching or exceeding \$1 billion.

This type of natural disaster can cause numerous negative effects, such as possible shortages of fuel supply for transport and power generation, damage to physical infrastructure, changes in energy demand, and widespread long-term interruptions to power grid users [8]. According to a recent study, US consumers experienced an average total of 8 h of power outages in 2020 [9], the highest figure since such a parameter has been recorded.

On the other hand, the appearance in December 2019 of the first cases of a new, previously unknown disease, later named COVID-19 by the World Health Organisation (WHO), were reported in the city of Wuhan, China. The pandemic caused by COVID-19 has had innumerable effects on many sectors of the global economy, such as agriculture, manufacturing, finance, education, health, energy, etc. [10].

One of the sectors where the pandemic has had the greatest influence has been the health sector, especially hospitals. Hospitals have played and continue to play a fundamental role in the fight against COVID-19. The pandemic created an unprecedented number of patients requiring admission to hospitals and intensive care units (ICUs) worldwide, especially in countries such as the USA [11], which in turn caused an increase in the demand for energy in hospitals around the world [12].

It is important to remember that hospitals are considered as one of the 16 critical infrastructures by the U.S. Department of Homeland Security (DHS) [13], which implies that their critical loads must have access to uninterrupted power, even in the event of sudden power outages [14], to ensure the surgical processes, the comfort and quality of life of patients, as well as the refrigeration of medicines and vaccines [8], especially at the present time when hospitals also serve as COVID-19 vaccination centres. Moreover, the main vaccines developed for the fight against COVID-19, such as different vaccines from Pzifer, Moderna or Janssen COVID-19, have high refrigeration requirements, as they require the use of freezers/refrigerators to store them at low temperatures (see Table 1) and to keep them at the right temperature until the time of administration. [15].

Table 1 Vaccine storage temperatures

Vaccine	Storage temperature °C
Pzifer-BioNTech	−70
Moderna	−25
Janssen COVID-19	2

Therefore, the increase in the number of natural disasters together with the increase in hospital pressure and energy demand caused by the COVID-19 pandemic, has

positioned hospitals as the main reference when analysing the importance of improving energy resilience in critical infrastructures, in order to guarantee the operation of their critical loads regardless of external events. For this reason, for this study we will focus on hospital facilities, specifically on the Chino Valley Medical Center located in the county of San Bernardino, in the US state of California, more specifically in Chino Valley.

Traditionally, diesel generators have been used in hospitals to provide backup power to critical loads in the event of power outages. However, diesel backup generators have a number of drawbacks in terms of resilience as: (i) they are rarely used and sometimes poorly maintained, so they may have problems in the time of a real emergency; (ii) they often have a limited supply of fuel, so if the supply disruption continues, more fuel must be supplied [16], which may be impossible in situations of natural disasters.

Furthermore, the decrease in recent years in both renewable energy (RE) and storage systems (BESS) costs [17, 18], has led to the increased use of microgrids, based on renewable energy (RE) and energy storage systems (BESS), to improve resilience in critical infrastructure, as the implementation of microgrids allows to isolate generation sources and local loads from a faulty grid and to operate independently for extended periods of time [19].

Therefore, the use of microgrids based on renewable energy (RE) and energy storage systems (BESS) can serve as an alternative or supplement to existing diesel generators in hospital facilities, extending limited fuel supplies and providing greater system redundancy [1]. Furthermore, it should not be forgotten that microgrids, when working connected to the grid, generate savings on electricity bills by reducing peak demand and energy costs [20].

After reviewing the scientific literature related to the subject matter of this article, the feasibility, benefits and

technical challenges of microgrids as sources of energy resilience have been evaluated in [21]. Also in [22] the advantages offered by the joint use (hybridisation) of generation systems together with energy batteries versus the individual use of both systems have been analysed. In addition, several papers [23–26] have described multiple methodologies to quantify the economic and energy resilience benefits, during a period of grid outage, provided by the implementation of a microgrid in different infrastructures such as airports, offices, telecommunication facilities, etc. Thus, other papers [8, 27–29] have followed the same methodological line but with the focus on critical hospital infrastructures, analysing multiple methodologies to quantify the financial and energy resilience benefits of implementing a microgrid based on renewable energies and energy storage.

It should be noted that, in most of the works referenced in the previous paragraph, the term Value of Lost Load (VoLL), a term related to the economic benefits of surviving a power outage, has not been mentioned or quantified. Other works such as those of Anderson et al. [1], Laws et al. [20], Rosales-Asensio et al. [30], have analysed the influence of such concept, its difficult quantification and have shown that the introduction of this value during resilience analysis has a significant impact on the economic viability and optimal size of a resilient microgrid.

Following the above, the work presented in this chapter aims to optimise a grid-connected microgrid, based on the implementation of a photovoltaic system and an energy storage system together with an existing backup diesel generator, to provide backup power to critical hospital loads during a 24-h outage with a minimum life cycle cost (LCC). The approach includes the influence of the COVID-19 pandemic on hospitals, a study of the lowest radiation month and the highest demand day of that month to select the day to simulate the outage, the assessment of the

probability of surviving an outage compared to business as usual (BAU), as well as the influence of placing an economic value on the resilience gained. Therefore, the contribution of this article is multiple: (i) the assessment of the economic viability of a grid-connected microgrid consisting of PV and batteries; (ii) the estimation of the optimal mix of technologies and dispatch strategies to reduce energy costs during a 24-h grid outage; (iii) an increase in the critical loads factor with respect to the default value used in this type of infrastructure due to COVID-19; (iv) the assessment of the probability of surviving power outages over a year compared to the business as usual (BaU) case; (v) the influence on the economic analysis of introducing avoided outage costs as a financial parameter.

The increase in the number of natural disasters in recent years, together with the effects caused by the emergence of COVID-19, has highlighted the need to study and improve the energy resilience of so-called critical infrastructures, especially those related to the health sector. Thus, after a brief overview of microgrids and energy resilience, of the different studies carried out and of the analysis objectives to be achieved throughout this work, the other three sections that make up this article will be briefly presented. In the second section “Materials and methods”, the case to be studied, the tool used for the simulation, as well as all the parameters to be introduced will be presented. In the third section “Results”, the different scenarios will be analysed and the results obtained for each of the scenarios will be presented. Finally, in the last section “Conclusions”, the final remarks and future lines of research will be presented.

2 Materials and Methods

This section describes the selected case study, the methodology, the simulation tool (REopt®) used to quantify the economic, and resilience benefits provided by a microgrid, and summarises the assumptions made and the main inputs to the analysis.

2.1 Case Study

As a case study, a hospital facility has been selected which, due to the health situation caused by COVID-19, also performs its functions as a vaccination centre. This factor increases the hospital's critical loads and the importance of interrupted power supply in the event of a power outage. For the present study, the Chino Valley Medical Center has been analysed. It is a private hospital located in Chino, California and was founded in 1972. Currently it has a total of 112 beds, an emergency department with 10 intensive care beds, full radiology and laboratory services, as well as an operating room with separate gastroenterology and pain facilities [31]. Chino Valley Medical Center's emergency department receives about 37,000 visits a year.

Although this is a case study, the characteristics and representativeness allow the results to be extrapolated to other critical facilities, especially those located in the United States.

2.2 REopt®

In this chapter we have used the REopt® optimisation tool provided by the National Renewable Energy Laboratory (NREL) to evaluate the optimal sizing of the different technologies that make up the microgrid, their optimal energy dispatch, as well as their ability to “survive” a power outage.

REopt® aims to solve a mixed-integer linear programme (MILP). The objective function minimises the total life cycle cost (LCC), which consists of a set of possible revenues and expenses over the analysis period defined, subject to a set

of integer and non-integer constraints to ensure that the thermal and electrical loads are satisfied at each point in time by some combination of the selected technologies [32].

For a complete analysis of the case study, two scenarios were simulated using the REopt® tool, as it allows scenarios with different energy objectives to be simulated. Firstly, a scenario based on minimising the life cycle costs (LCC) of the installation without any interruption to the grid, i.e. during normal grid operation, has been simulated. Secondly, a 24-h grid interruption scenario was simulated. Thus, REopt® optimally sizes the selected technologies for grid-connected operation (LCC minimisation), while at the same time ensuring the maintenance of critical loads during a pre-defined grid interruption period [33].

It should be noted that REopt® solves a single year optimisation to determine future cash flows for N years, assuming constant production and consumption over the N years set for the desired analysis [33].

For a more detailed description of the main points regarding the REopt® tool, please refer to Ref. [32, 33]. The online tool can also be found at [34].

2.3 Model Data and Assumptions

In the following subsections, all the inputs of the model will be detailed together with the technical-economic hypotheses that have been used, and the references consulted to assume these hypotheses will also be specified.

A summary of the main inputs and outputs used by REopt® can be seen in Fig. 1.

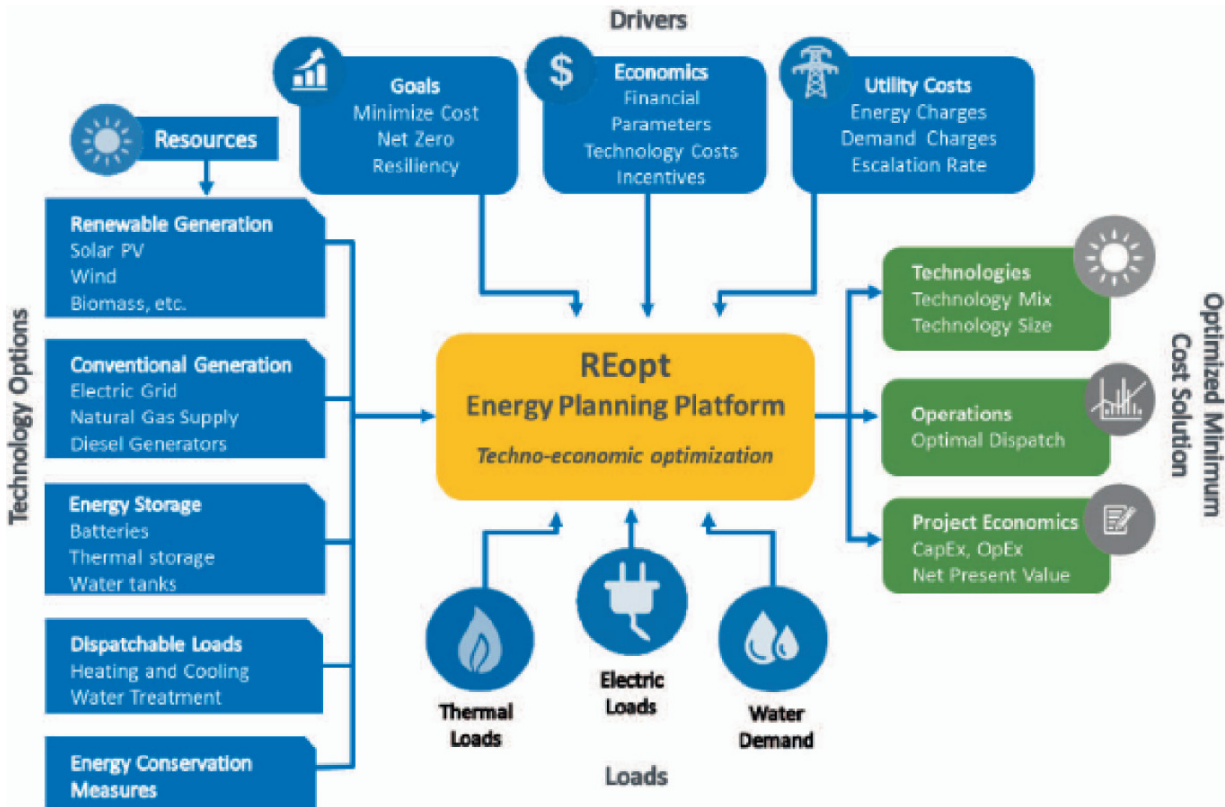


Fig. 1 Summary of the main inputs to and outputs from REopt model. *Source [33]*

2.3.1 Location and Electricity Tariff

For the simulation, a critical infrastructure has been selected, such as a hospital, located in the city of Chino, California (USA) (Table 2).

Table 2 Inputs and outputs for the site and utility

Site and utility		
Parameters	Value	Reference
Site location	Chino, California	–
Latitude	34.02557	–
Longitude	–117.685639	–
Land available (acres)	Unlimited	–
Roof space available (sq. ft)	Unlimited	–

Site and utility		
Parameters	Value	Reference
Electricity rate	Southern California edison company: time-of-use—general service—large: TOU—8 CPP (2-50 kV)	[35]
Net metering system size limit (kW)	0	–
Wholesale rate (\$/kWh)	0	–

Source Own elaboration

In relation to the electricity tariff, the Southern California Edison electricity company is one of the companies responsible for supplying energy to the city of Chino, California. In view of the hospital's characteristics and energy demand, the “Time-Of-Use—General Service—Large: TOU—8 CPP (2-50 kV)” tariff was used for this analysis. According to this tariff, the service voltage must be less than 50 kV and the peak demand cannot exceed 4 MW [36].

Furthermore, this tariff promotes the installation of photovoltaic energy since, observing the hourly distribution of the different periods for both energy and power, the periods with the highest economic load, such as P4 and P5 for the energy consumed and P3 for the power term, are located in the hours of highest solar production. The electricity tariff applied to this study is presented in detail in Table 3 [35].

Table 3 Applied electric tariff

Southern California Edison company: time-of-use—general service—large: TOU—8 CPP (2-50 kV)	
Parameter	Value
Fixed charge [\$/month]	319.47
Seasonal/monthly demand charge structure [\$/kW]	14.88

Southern California Edison company: time-of-use—general service—large: TOU—8 CPP (2-50 kV)	
Parameter	Value
<i>Time of use demand charge structure</i>	
Period 1 (P1) [\$/kW]	0
Period 2 (P2) [\$/kW]	6.41
Period 3 (P3) [\$/kW]	23.24
Demand reactive power charge [\$/kVAr]	0.51
<i>Tiered energy usage charge structure</i>	
Period 1 (P1) [\$/kWh]	0.06426
Period 2 (P2) [\$/kWh]	0.08397
Period 3 (P3) [\$/kWh]	0.05902
Period 4 (P4) [\$/kWh]	0.08222
Period 5 (P5) [\$/kWh]	0.1351

Source [35]

2.3.2 Load Profile

The load profile of the simulated building will be evaluated for a full year and a consumption of 3,228,120 kWh/year has been estimated. In order to estimate this consumption, it has been used Ref. [37], where the energy consumption of a hospital is analysed according to its climatic zone. For the case of a Mediterranean climate, similar to certain areas of California, an electricity consumption per bed of 26,460 kWh/bed is indicated. The typical load profile shown in Fig. 2, is simulated based on the DOE Commercial Reference Building Hospital model for the California climate zone [38].

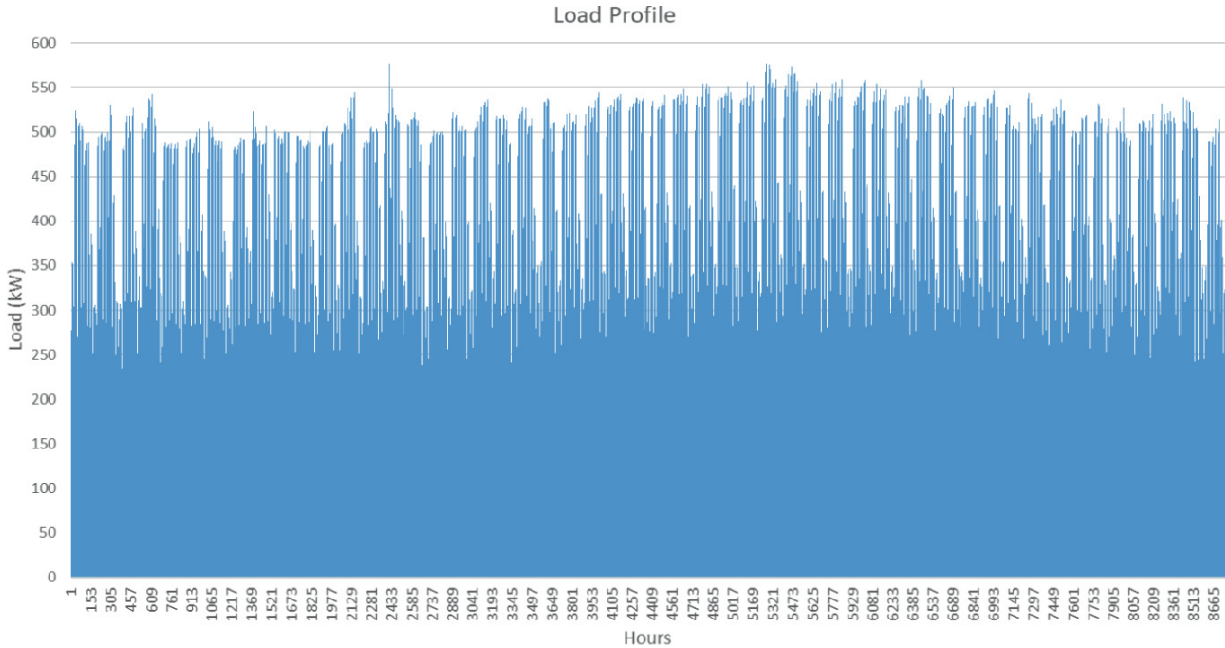


Fig. 2 Annual load demand of the hospital. *Source* [37, 38]

The average daily load is 368.51 kW, with a minimum load of 225.70 kW in February and a maximum load of 577.07 kW in April. Table 4 shows in detail the values related to the load profile entered in the model.

Table 4 Inputs and outputs related to the load profile

Load profile		
Parameters	Value	References
Building type	Hospital	-
Load profile	Simulated	[38]
Annual energy consumption (kWh)	3,228,120	[37]

Source Own elaboration

2.3.3 Resilience

The interruptions in the electricity grid are defined by their duration (in hours), their date and their start time [8]. For the energy resilience analysis, an interruption period of the electricity grid has been selected that will only occur once a year. This interruption will have a duration of 24 h, a

start time of 1 a.m. and will take place on 18 December. As can be seen in Fig. 3, December is the month of the year with the lowest solar radiation and the 18th of that month is the day with the highest load (538.72 kW). This allows us to simulate and quantify the microgrid in the most adverse scenario (period of highest load and lowest solar radiation). In addition, the microgrid must be able to supply the hospital's critical loads during the interruption period. For this analysis, the new scenario in terms of energy caused by COVID-19 [11, 15, 39], has been taken into account, so it has been decided to increase the critical loads factor to 60%. In other research in the area of resilience in healthcare buildings, a factor of 50% has been used, but under the current paradigm, we believe this falls short, which is why we have decided to increase this factor to 60%. The resilience values introduced in the model are shown in detail in Table 5.

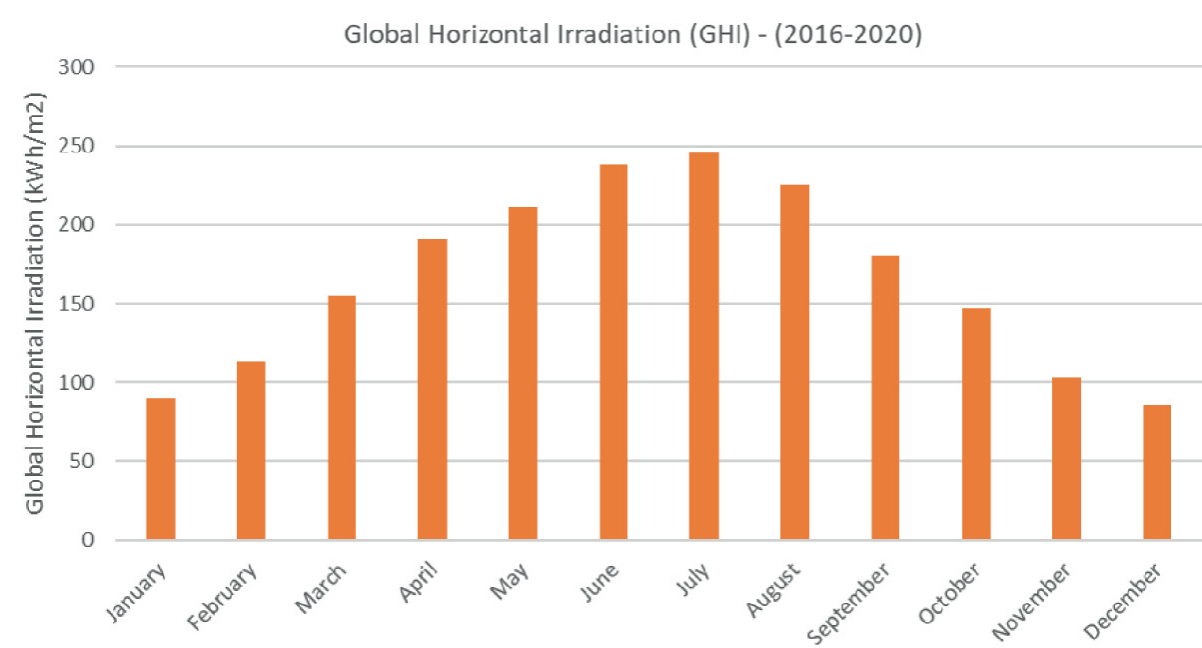


Fig. 3 Average global horizontal irradiation in Chino, US. Source [45]

Table 5 Inputs and outputs related to the resilience

Resilience		
Parameters	Value	References
Critical load factor (%)	60	–
Outage durations (hours)	24	–
Outage start date	December 18	–
Outage start time	1 AM	–

Source Own elaboration

In addition, for a more complete analysis in terms of energy resilience, we will also assess the amount of time the optimised microgrid can survive grid interruptions over a year.

Finally, it is very important to highlight the role of quantifying the avoided outage costs when analysing a resilience investment. That is, the avoided outage costs are the losses that the site would experience if the critical load were not covered [32]. This is probably the most difficult value to quantify, due to lack of data and government policy [40]. In order to quantify this, the most common parameter used is the value of lost load (VoLL), which can include loss of assets, damage to machinery, business outage costs and outage costs [41], which is expressed in \$/kWh. Therefore, the avoided outage costs are calculated by multiplying the value of the lost load (VoLL) in \$/kWh by the average number of hours that the critical load can be fed by the microgrid, and multiplying by the average critical load [32].

For the purpose of this analysis, a value of the lost load (VoLL) of \$12.7 per kWh has been considered. This value is taken from Ref. [42], for an outage of 16 h. It is necessary to indicate that our outage has a duration of 24 h, so the VoLL for our case may have a higher value, since it covers a total of eight hours more than the sixteen hours of the chosen value. However, due to the complexity of quantifying the VoLL, it has been decided to take the closest value specified in Ref. [42].

2.3.4 Financial Parameters

A period of 20 years has been selected for the financial analysis, which is the time we have considered to be the useful life of the main equipment that forms the microgrid.

On the other hand, we have assumed an increase in the nominal cost of electricity of 2.3% and an increase in the nominal cost of fuel of 2.7%. Table 6 shows in detail the financial values introduced in the model.

Table 6 Inputs and outputs related to the financial analysis

Financial		
Parameters	Value	References
Analysis period (years)	20	–
Nominal host discount rate (%)	8.3	[43]
Nominal electricity cost escalation rate (%)	2.3	[44]
Nominal generator fuel cost escalation rate (%)	2.7	[44]
Host effective tax rate (%)	26	[43]
O&M cost escalation rate (%)	2.5	[43]

2.3.5 Photovoltaic System

To obtain the electricity generation produced by the PV system, REopt® uses the PVWatss application of the NREL [32]. The total energy produced by the PV system at any given time is proportional to the hourly capacity factors of the site. Figure 3 shows the monthly radiation levels for the town of Chino, California and it can be seen that the month with the lowest radiation is December, the month that will be chosen for the study of the energy resilience scenario. The solar radiation data has been obtained from PVGIS®, an online tool developed by the Joint Research Centre of the European Commission [45].

For this analysis we have assumed that the photovoltaic modules will be of standard type and that they will be installed on the roof of the building, they will be anchored

to it by using specialised photovoltaic structures for roofs and will have an orientation of 0° to the South and an inclination of 10° with respect to the roof's ground.

According to [43] an investment cost of 1600 \$ per kW installed and a system O&M cost of 16 \$ per kW installed has been assumed. In addition, we have assumed overall system losses of 14%, caused by soiling, shading, mismatch, wiring, light-induced degradation (LID), availability, etc. Table 7 shows in detail the values related to the PV system introduced in the model.

Table 7 Inputs and outputs related to the PV module

Solar PV module		
Parameters	Value	References
System capital cost (\$/kW)	1600	[43]
Minimum new PV size (kW DC)	0	–
Maximum new PV size (kW DC)	Unlimited	–
O&M cost (\$/kW per year)	16.0	[43]
Module type	Standard	[46]
Array type	Rooftop, fixed	[46]
Array azimuth (deg)	180.0	[46]
Array tilt (deg)	10.0	–
DC to AC size ratio	1.2	[46]
Systems losses (%)	14.0	[46]
Federal percentage-based incentive (%)	26.0	[47]
Incentive duration (years)	1	[47]
MACRS schedule (years)	5	[47]
MACRS bonus depreciation (%)	100	[47]

2.3.6 Energy Storage System

Energy storage technologies are aimed to capture revenue through different alternatives such as: (i) demand cost reduction or “peak shaving”; (ii) time-shifting excess

renewable energy production; (iii) performing energy arbitrage [32].

For the analysis we have assumed that the energy storage system is based on the characteristics of a lithium-ion battery. REopt® models energy storage systems as “reservoirs”, where the energy produced at one point in time can be consumed at another time [33]. We have also assumed a minimum state of charge (SoC) of 20%, while a value of 50% has been taken for the initial state of charge. According to Mongird et al. [48], the lifetime of lithium batteries is in the range of 10–20 years. In this case, it has been considered that the grid can charge the batteries if necessary. Table 8 shows in detail the values related to the energy storage system introduced in the model.

Table 8 Inputs and outputs related to the energy storage system

Energy storage system		
Parameters	Value	References
Energy capacity cost (\$/kWh)	420.0	[49]
Power capacity cost (\$/kWh)	840.0	[49]
Allow grid to charge battery	Yes	–
Minimum energy capacity (kWh)	0.0	–
Maximum energy capacity (kWh)	Unlimited	–
Energy capacity replacement cost (\$/kWh)	200.0	[49]
Energy capacity replacement year	10	[50]
Power capacity replacement cost (\$/kW)	410.0	[49]
Power capacity replacement year	10	[50]
Minimum power capacity (kW)	0.0	–
Maximum power capacity (kW)	Unlimited	–
Rectifier efficiency (%)	96.0	[51]
Round trip efficiency (%)	97.5	[51]
Inverter efficiency (%)	96.0	[51]
Total AC-AC round trip efficiency (%)	89.9	[51]

Energy storage system		
Parameters	Value	References
Minimum state of charge (%)	20.0	[51]
Initial state of charge (%)	50.0	–
MACRS schedule (years)	7	[52]
MACRS bonus depreciation (%)	100	[52]

2.3.7 Back-Up Diésel Generator

For the analysis, it has been assumed that the hospital has a back-up unit consisting of a 400 kW diesel generator. We have assumed that the generator has a tank capacity of 660 gallons (2498.37 L) and a lifetime of 10 years. The back-up diesel generators will not involve any capital cost, as they are already in place.

The diesel generator will only operate in the event of an outage in the electricity grid, as by law it can only be operated in emergencies [33] to supply the critical loads of the building. Table 9 shows the detailed values entered in the model.

Table 9 Inputs and outputs related to the back-up generator

Generator		
Parameters	Value	References
Install cost (\$/kW AC)	500.0	[53]
Diesel cost (\$/gal)	3.0	[53]
Fuel availability (gallons)	660	[54]
Existing diesel generator	Yes	–
Existing diesel generator size (kW)	400.0	–
Fixed O&M cost (\$/kW per year)	10.0	[53]
Variable O&M cost (\$/kWh)	0.0	[53]
Fuel burn rate (gallons/kWh)	0.076	[55]
Generator replacement year	10	–

3 Results and Discussion

This section presents the main results obtained from the different simulations carried out using REopt® software. Two different scenarios have been considered in this study.

- **Normal operation of the grid.** This scenario will serve as an introductory thread, as the main objective of the study is to analyse the energy resilience provided by the microgrid. Thus, only the optimal sizing and dispatch of the microgrid will be analysed from purely economic criteria, without any resilience requirements. It should be specified that this scenario does not take into account the presence of a back-up diesel generator.
- **Optimal sizing of a microgrid with resilience requirements.** This is the main scenario of the paper and the one on which we have spent the most effort. In this scenario, the hybrid microgrid will be optimised with the consideration of feeding the critical loads during a 24-h outage in the month of December. This scenario aims to analyse the following aspects: (i) optimal sizing and dispatching of the microgrid for a 24-h outage; (ii) the analysis and comparison of the amount of time the microgrid optimised by REopt® can survive grid outages over the year compared to the BAU case; (iii) the economic valuation of the energy resilience provided by the microgrid. For this scenario, the existence of a 400 kW back-up generator at the hospital has been assumed.

The main characteristics of these scenarios can be seen in Table 10.

Table 10 Main simulation scenarios

Scenario	Optimized from	Interruption duration	Diesel generator	Resiliency economic valuation
1	Economic perspective	N/A	No	No
2	Resilience perspective	24 h	Yes	Yes

3.1 Scenario 1: Normal Operation of the Grid

As mentioned above, the main objective of this scenario is to obtain the optimal sizing and energy dispatch of the microgrid, consisting only of a photovoltaic system and an energy storage system, from an economic point of view. Consequently, the microgrid is optimised to maximise the economic benefits during its normal grid operation.

The results provided by REopt®, in relation to the optimal size of the microgrid, shows that the simulated hospital is able to minimise its energy cost by installing a microgrid based on a photovoltaic system of 796 kW peak power and an energy storage system of 263 kWh capacity and 115 kW nominal power. Before the installation of the microgrid, the simulated hospital presented an average annual energy supplied by the grid of 3,228,120 kWh, after the installation of the microgrid, the grid supply has become a value of 2,090,512 kWh. In this way, the microgrid provides to the hospital with 35% of the total annual energy consumed and a saving in the electricity bill of \$146,295 per year.

For this scenario, the main financial results provided by REopt® that will be taken into account are: (i) Net Present Value (NPV); (ii) Payback period; (iii) Levelized Cost of Energy (LCOE). First, when we refer to Net Present Value (NPV), we refer to the difference between the life cycle cost of the optimised case and the life cycle cost of the Business as Usual (BaU) case [32], case without the microgrid installation. The life cycle energy cost without

microgrid (BaU) is \$3,580,027, while with the implementation of the microgrid proposed by REopt® it is \$3,328,145. Thus, the Net Present Value (NPV) of the investment is \$251,882. Second, the payback of the investment is 7.42 years. Finally, the Levelized Cost of Energy (LCOE) value is \$0.071/kWh.

Figure 4 shows the optimised energy dispatch for the Chino Valley Medical Center after the installation of the optimised microgrid during its normal grid operation, both in the month of lowest solar radiation and in the month of highest solar radiation.

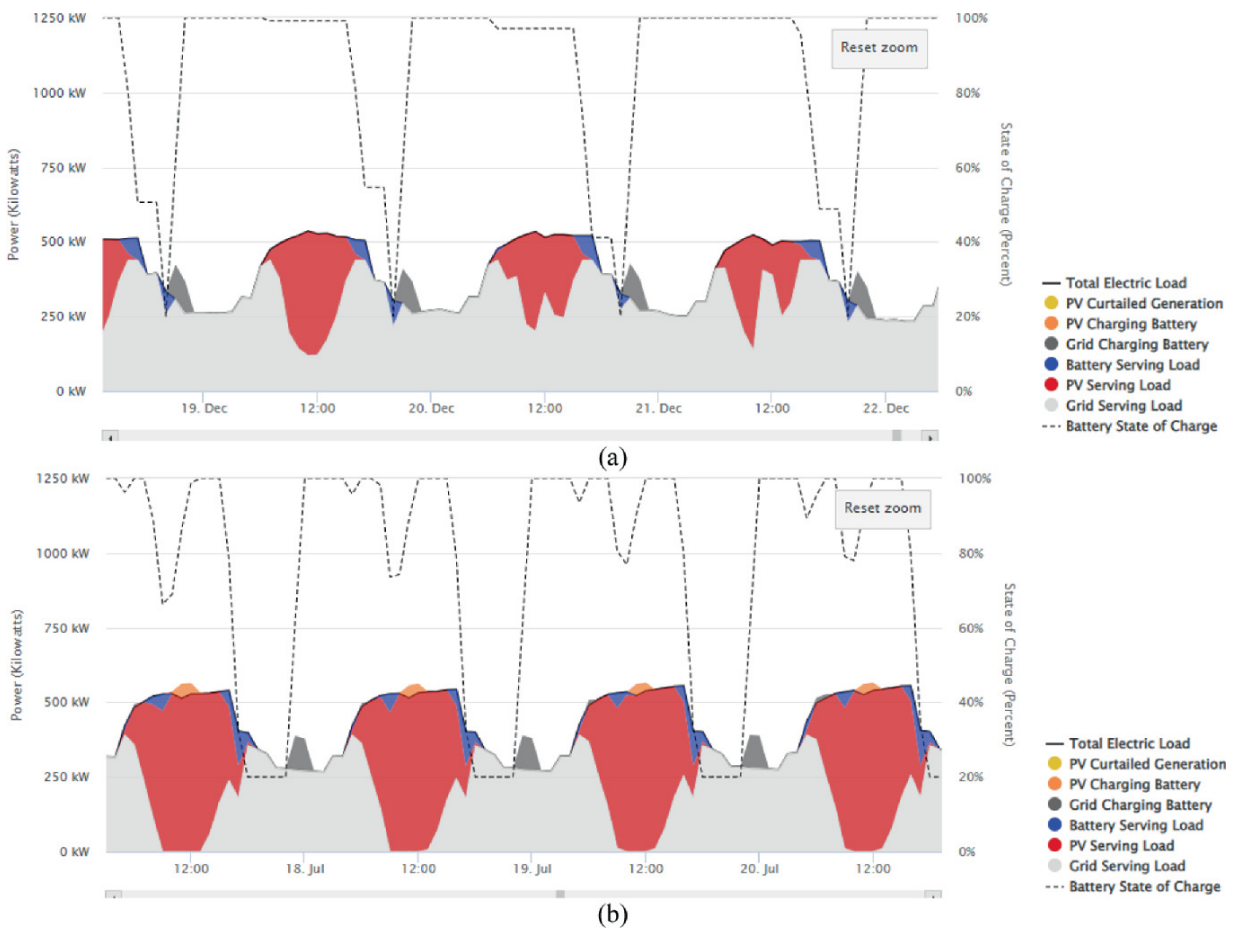


Fig. 4 Energy dispatch of microgrid under: **a** Winter and **b** summer

Figure 4a shows how the energy dispatch of the different technologies is carried out in the month with the

lowest radiation. In general terms, the microgrid, consisting of the photovoltaic system and the energy storage, works in a coordinated way to cover the demand for electrical energy of the hospital, minimising the electrical energy imported from the grid. During the hours when there is solar resource in the month of lower solar radiation, the photovoltaic system alone is not able to cover the entire electricity demand of the hospital, so the grid supplies the remaining portion. As the objective of the microgrid is to meet the hospital's demand at the lowest possible cost, the energy dispatch provided by REopt® prioritises the production of the photovoltaic system over the energy storage, which only comes into operation at certain times of the day. Energy storage is discharged between 3 and 8 p.m. when photovoltaic generation is decreasing and the price of energy provided by the grid is still high, thus slightly reducing peak demand and achieving saving. Normally, the battery is charged when its state of charge (SoC) reaches its minimum value, which in this case is 20% and, on the other hand, it is usually charged from the grid when the cost of electricity is minimal. In this case, from 9 p.m. the price of electricity reaches a minimum value, at which time the battery is charged from the grid.

Figure 4b shows the equivalent energy dispatch, but for the month with the highest solar resource. As can be seen, the behaviour of the microgrid is different with respect to Fig. 4a. Between 9 a.m. and 1 p.m., the photovoltaic system is able to meet the entire electricity demand of the hospital and even has surpluses that are used to charge the energy storage, something that did not happen in the previous case. During the night, it is the grid that provides the electricity supply. Energy storage injects energy both in the morning and in the late afternoon, when the price of energy is in periods of high prices and photovoltaic generation is losing importance due to the lack of solar resources in the

late afternoon. Therefore, both in the month with the lowest solar resource and in the month with the highest, energy storage has performed the function of reducing peak demand (peak shaving) as well as energy arbitrage, charging from the grid at times when the price of energy is minimal, and from the photovoltaic surplus in the months with the highest solar resource, and injecting energy into the microgrid at times with the highest energy consumption and the highest energy price.

3.2 Scenario 2: Microgrid with Resilience Requirements

In this scenario, REopt® optimises the microgrid to meet the hospital's energy demand with the minimum life cycle, with the additional constraint that the hospital's critical load must be met during a 24-h outage period. A critical load for the hospital of 60% has been assumed. The simulation carried out for the resilience requirements suggests a microgrid consisting of a 799 kW peak power photovoltaic system and an energy storage system with 280 kWh capacity and 118 kW nominal power to complement the 400 kW diesel backup generator, which already existed in the hospital.

Table 11 summarises and compares the techno-economic parameters of the optimal case with resilience requirements with the Business as Usual (BaU) case. There is a decrease of 1,139,129 kWh in electricity demand from the grid. The life cycle energy costs of the optimal case have a value of \$3,365,120, resulting in an NPV of \$254,531. It is calculated as the difference between the life cycle energy cost of the Business as Usual (BaU) case and the life cycle energy cost of the optimised case [32], a positive NPV indicates that the project is economically feasible.

Table 11 Techno-economic comparison between the BaU and optimal resilience

	Business as usual	Optimal resilience	Difference
<i>System size and energy production</i>			
PV size	0 kW	799 kW	799 kW
Battery power	0 kW	118 kW	118 kW
Battery capacity	0 kWh	280 kWh	280 kWh
Generator size	400 kW	400 kW	0 kW
Average annual PV energy production	0 kWh	1,179,691 kWh	1,179,691 kWh
Average annual energy supplied from grid in year 1	3,218,106 kWh	2,078,977 kWh	1,139,129 kWh
<i>Utility cost (year 1)—before tax</i>			
Utility energy cost	\$248,609	\$150,334	\$98,275
Utility demand cost	\$163,920	\$114,841	\$49,079
Utility fixed cost	\$3834	\$3834	\$0
Utility minimum cost adder	\$0	\$0	0
Total year 1 utility cost	\$416,363	\$269,009	\$147,354
<i>Life cycle cost</i>			
CAPEX + replacements	\$0	\$903,528	\$903,528
O&M costs	\$34,912	\$146,489	\$111,577
Generator fuel costs	\$11,731	\$6611	\$5120
Total utility electricity cost	\$3,573,007	\$2,308,492	\$1,264,515
<i>Summary financial</i>			
Life cycle energy cost (LCC)	\$3,619,651	\$3,365,120	\$254,531
Net present value (NPV)	\$0	\$254,531	\$254,531

Figure 5 shows the optimised power dispatch during the 24-h power outage for the Chino Valley Medical Center facilities. In Sect. 2. Materials and Methods the main inputs related to the resilience scenario are detailed. In summary, the blackout starts at 1:00 a.m. on 18 December and ends at the same time on 19 December. In order to be

conservative, the case has been analysed for the worst-case scenario: the month with the lowest solar resource and the day of that month with the highest demand. Finally, it should be noted that during the outage, the hospital's electrical load decreases to its critical value, which has been set at 60, 10% higher than the usual value used in energy resilience analyses for hospitals.

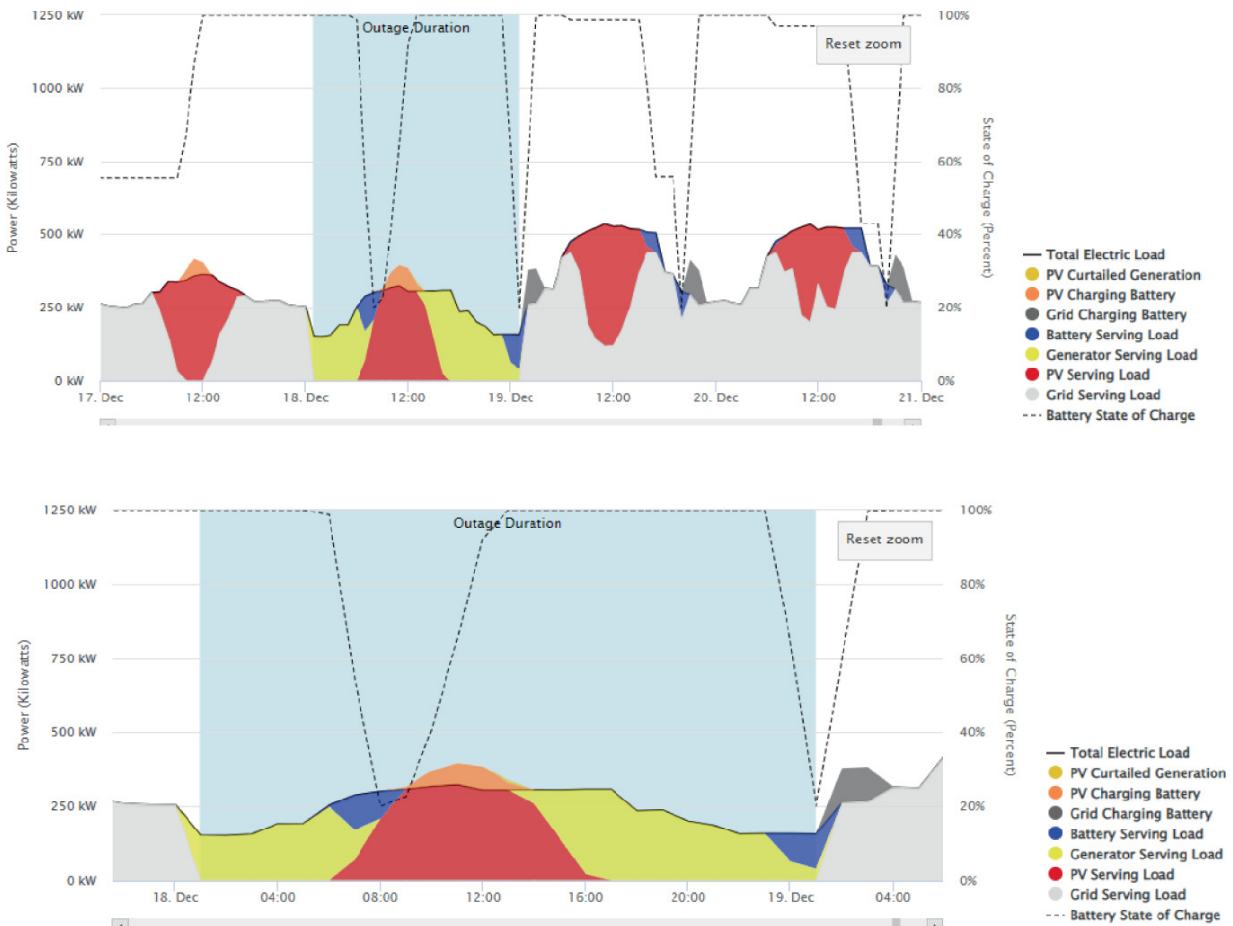


Fig. 5 Energy dispatch on December 18st with a blackout at 1 a.m. for 24 h

During the outage, the diesel backup generator plays a major role in the hours where PV generation is zero. Thus, it covers the entire critical load during the first hours of the outage, which correspond to the hours where solar generation is zero. On the other hand, energy storage plays a minor role in the energy dispatch. Energy storage feeds the critical loads of the hospital between 6 and 9 a.m.,

when photovoltaic generation is not yet high enough to meet the load on itself. Once the BESS reaches its minimum SoC value, it stops feeding the critical loads. From that moment on, the photovoltaic generation is responsible for supplying all the electricity to the hospital's critical loads, allowing the back-up diesel generator to stop operating. During the period when the photovoltaic system has surplus energy, this surplus energy is used to charge the energy storage. The back-up diesel generator comes back on line at 1 p.m. with a minimal role, and it supplies the hospital's entire electricity demand from 4 p.m. onwards, when the photovoltaic generation reaches its minimum generation. From this moment, the back-up diesel generator supplies the full load until the end of the outage. One aspect that should not be ignored is how in the last two hours of outage, the energy storage system enters into operation for two main reasons. On the one hand, it reduces the electrical demand of critical loads, thus applying peak shaving and making the back-up diesel generator save fuel in the last two hours of the outage period. On the other hand, the time when the outage ends corresponds to the time when energy has a lower price, so the energy storage system takes advantage of the last two hours to discharge to the maximum allowed and once the outage period is over it continues with its operating strategy, which is to charge from the grid in the hours when energy has a minimum economic value. This behaviour has been detailed in the previous scenario, highlighting the role of energy storage as a method of energy arbitrage and peak shaving.

The microgrid scheme provided by REopt® allows the hospital to “survive” the 24-h outage (see Fig. 5), providing a secure power supply, which allows to continue with the main activity of the hospital centre. It should be noted that the microgrid has been optimised to supply the critical loads of the hospital during a specific outage period, but as

both the load profile of the hospital and the solar resource are variable throughout the year, the microgrid may not be able to sustain the same outage at another time in the year. Therefore, in order to ensure that the microgrid meets resilience requirements throughout the year, we have simulated that outages occur from every hour of the year (8760 simulations) and REopt® has calculated the amount of time the microgrid can sustain the critical load during every outage [32].

The results are shown in Table 12, and indicate that not only does our microgrid withstand the outage we have proposed, but it is capable of withstanding in all cases an average of 72 h of energy self-supply capacity, with a maximum of 108 h and a minimum of 41 h, much higher than the business as usual (BaU) case.

Table 12 Hours of system survival

	Business as usual	Resilience
Survives specified outage	YES	YES
Average time	39 h	72 h
Minimum time	31 h	41 h
Maximum time	54 h	108 h

Through this simulation, we have also observed how the addition of the microgrid consisting of a photovoltaic system with 799 kW peak power and an energy storage system with 280 kWh capacity and 118 kW nominal power to the existing installation, consisting of a 400 kW diesel backup generator, has increased the net resilience of the Chino Valley Medical Center. The Fig. 6 shows the number of outage hours that business as usual (with only the 400 kW backup generator) can withstand compared to the optimised microgrid (combination of photovoltaic system, energy storage and existing generator). Considering a fixed fuel supply and that no additional fuel supply is made

during the outage, business as usual (BaU) has a 90% probability of surviving simulated outages of over 34 h. In the optimal case (Microgrid + Backup diesel generator), there is a 90% probability of surviving the simulated outages of over 58 h. Thus, by implementing the microgrid, the hospital achieves a net gain in resilience of 24 h compared with business as usual (BaU), this is due to the decrease in fuel consumption, because during the hours where the PV generation is able to supply the critical loads on its own, the backup diesel generator does not operate, avoiding higher fuel consumption and extending the survival time of the system as a whole.

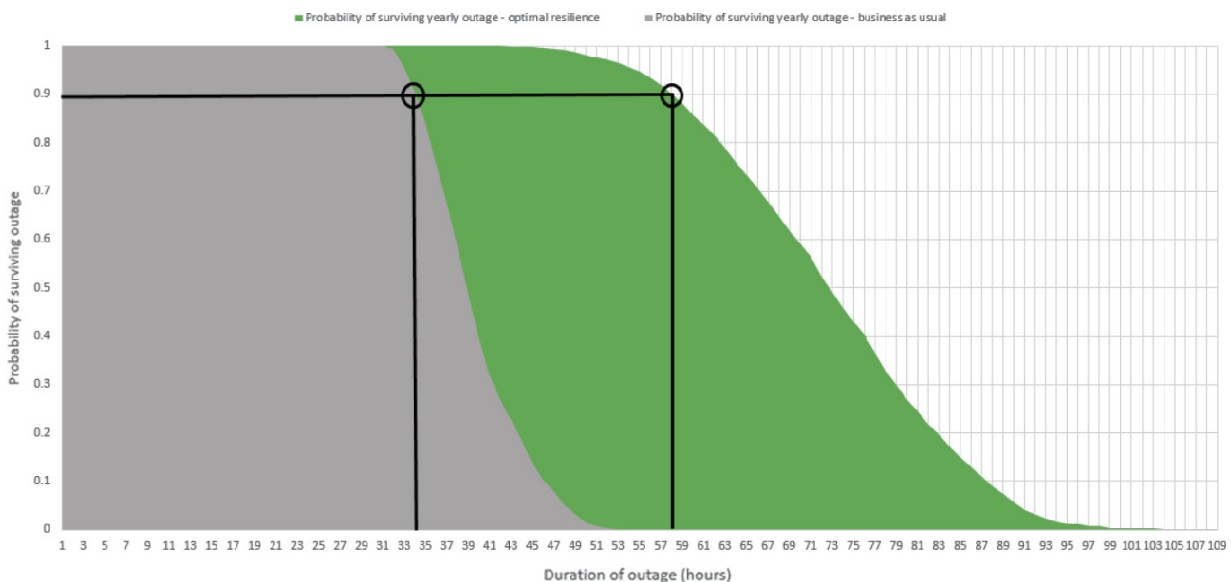


Fig. 6 Outage survival probability for the optimal resilience and business as usual cases.

Source Own elaboration

In most cases, attention is only focused on the question of whether the optimised microgrid is able to “survive” the outage period introduced and, on the other hand, whether it is economically viable over its lifetime, by comparing the Net Present Value (NPV) of the business as usual (BaU) case with the value of the optimal case. However, the economic benefits that can be gained from investing in an energy resilient system are neglected.

Therefore, in order to have a picture of the economic benefits in terms of energy resilience, it is necessary to put a financial value on the avoided outage costs of the microgrid. As explained in Sect. 2.3.3, in order to quantify these avoided costs, it is necessary to apply the following mathematical Eq. (1):

$$\text{Avoided outage costs} = \text{VoLL} \cdot \text{Hrs}_{\text{average}} \cdot \text{Load}_{\text{average}} \cdot \%_{\text{critical load}} \quad (1)$$

A value of lost load (VoLL) of \$12.7/kWh, an average survival period of 72 h, an average hospital consumption of 368.51 kW and a critical load factor of 60% have been considered. All these data can be found in detail in Sect. 2. Materials and Methods. The Fig. 7 shows the result obtained. Therefore, the avoided outage costs amount to a total of \$202,179, which translates into an increase in the Net Present Value of more than 79% with respect to the Net Present Value of the case without valuing the energy resilience provided by the microgrid.

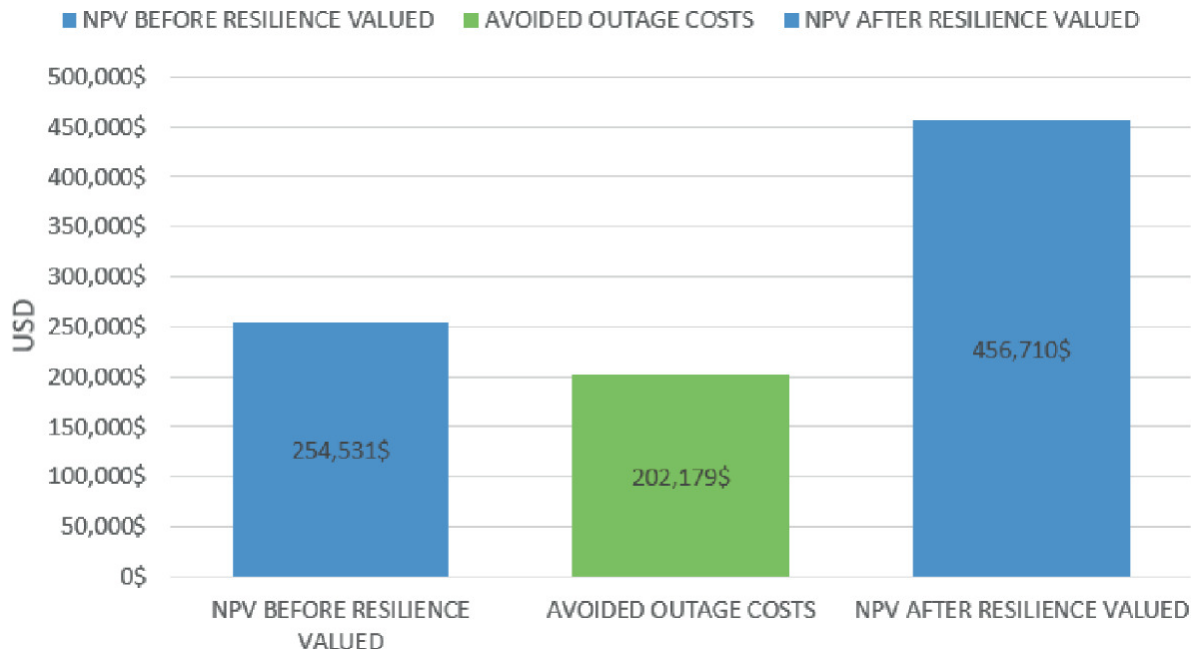


Fig. 7 Effect of resilience costs and benefits.

Source Own elaboration

Finally, it should be noted that the results obtained do not take into account the costs of investment in additional hardware and software to make the microgrid work in both grid-connected and island mode. But we would like to make it clear that these costs can vary widely and can range from a minimum of 10% and a maximum of 50% of the total cost of the non-islandable system cost [20]. Thus, Laws et al. [20], investigates how to quantify the cost of investing in a microgrid that can work in island mode and determines that, although it is a difficult task, it is possible to establish a maximum cost that allows us to know whether or not the investment is economically viable compared to the case without island mode. Therefore, the maximum investment cost of an islanded microgrid is the NPV of the scenario with valued resilience (outage costs avoided), minus the NPV of the scenario without valued resilience (no outage costs avoided).

4 Conclusions

The objective of the research presented here is to assess the energy resilience, both in technical and economic terms, provided by a microgrid during a 24-h outage of the electricity grid. The pandemic caused by COVID-19 has led to changes in many sectors of the economy and society, one of them being the health sector. The high number of patients hospitalised due to COVID-19, together with the massive vaccination campaigns carried out in hospitals, has led to an increase in energy demand and with it an increase in both their critical loads and the need to supply them in the event of possible network outages. In this situation, a hospital has been taken as a case study, in which two scenarios with different approaches have been analysed using the simulation tool REopt®. A first scenario, without any resilience requirements, where the size and optimal energy dispatch of the microgrid in the month of lowest

and highest solar radiation has been analysed. The results of the analysis have shown how a microgrid consisting of a 796 kW photovoltaic system and an energy storage system with 263 kWh capacity and 115 kW nominal power is able to provide an NPV of \$251,882. It has also been shown that only in months of high solar radiation the energy storage is charged from the PV system, while in months of low solar radiation the energy storage is only charged from the grid when energy prices are at their lowest. For the second scenario with resilience requirement, not only a 24-h outage has been introduced in the month of lowest solar radiation and on the day of highest load, but also, due to COVID-19, the critical load factor of the hospital has been increased to 60%. Thus, the results have shown that the microgrid optimised by REopt® is able to provide an NPV of \$254,531 over its 20-year lifecycle and is not only able to withstand the specified outage, but is able to withstand it at any time of the year, providing the hospital with a net gain of 24 h in terms of energy resilience compared to business as usual case (BaU), thanks to the reduction in fuel consumption during grid outages. If the net gain provided by the microgrid is to be made profitable, the avoided outage costs should be valued. The quantification of these costs and their posterior analysis have resulted in an increase of 79% of the NPV. To summarise, it has been observed that the different variables introduced in the model and the different approaches play a critical role in determining the viability of a microgrid, so each case study must be evaluated individually. Finally, for future research work, it would be interesting to establish a methodology to quantify the additional costs involved in upgrading the microgrid to enable it to operate in island mode during an outage of the grid, providing a more objective view when deciding on the investment.

References

1. Anderson K et al (2018) Quantifying and monetizing renewable energy resiliency. *Sustainability* 10(4):933. <https://doi.org/10.3390/su10040933> [Crossref]
2. The National Association of State Energy Officials (NASEO) (2009) *State Energy Assurance Guidelines*
3. McAllister T (2015) *Community resilience planning guide for buildings and infrastructure systems, volume I*. In: Special publication (NIST SP). National Institute of Standards and Technology, Gaithersburg, MD. <https://doi.org/10.6028/NIST.SP.1190v1>
4. Hotchkiss EL, Dane A (2019) *Resilience roadmap: a collaborative approach to multi-jurisdictional resilience planning*. National Renewable Energy Lab. (NREL), Golden
5. Phillips J, Finster M, Pillon J, Petit F, Trail J (2016) *State energy resilience framework*. Argonne National Lab.(ANL), Argonne
6. Prowler D, Vierra S (2008) Whole building design. *Whole Build Des Guid Natl Inst Build Sci* 2:3252
7. NOAA National Centers for Environmental Information (NCEI) (2022) U.S. billion-dollar weather and climate disasters. <https://doi.org/10.25921/stkw-7w73>.
8. Reyes-Ascanio A, Colmenar-Santos A, Pérez-Molina C, Rosales-Asensio E (2021) Application of microgrids to improve resilience with a focus on healthcare. In: *Proceedings of the 2021 4th Asia conference on energy and electrical engineering (ACEEE)*, pp 49–57. <https://doi.org/10.1109/ACEEE51855.2021.9575058>
9. Energy Information Administration (EIA) (2021) U.S. electricity customers experienced eight hours of power interruptions in 2020. <https://www.eia.gov/todayinenergy/detail.php?id=50316>. Accessed 21 Mar 2022
10. Nicola M et al (2020) The socio-economic implications of the coronavirus pandemic (COVID-19): a review. *Int J Surg* 78:185–193. <https://doi.org/10.1016/j.ijssu.2020.04.018> [Crossref]
11. Barbash IJ, Kahn JM (2021) Fostering hospital resilience—lessons from COVID-19. *JAMA* 326(8):693–694. <https://doi.org/10.1001/jama.2021.12484> [Crossref]

12. Jiang P, Van Fan Y, Klemeš JJ (2021) "Impacts of COVID-19 on energy demand and consumption: challenges, lessons and emerging opportunities. *Appl Energy* 285:116441. <https://doi.org/10.1016/j.apenergy.2021.116441> [Crossref]
13. U.S. Department of Energy (2019) Distributed generation (DG) for resilience planning guide
14. Liu J, Jian L, Wang W, Qiu Z, Zhang J, Dastbaz P (2021) The role of energy storage systems in resilience enhancement of health care centers with critical loads. *J Energy Storage* 33:102086. <https://doi.org/10.1016/j.est.2020.102086> [Crossref]
15. Santos AF, Gaspar PD, de Souza HJL (2021) "Refrigeration of COVID-19 vaccines: ideal storage characteristics, energy efficiency and environmental impacts of various vaccine options. *Energies* 14(7):849. <https://doi.org/10.3390/en14071849> [Crossref]
16. Lawrence B, Hancock M, Stieva G (2010) How unreliable power affects the business value of a hospital. White Pap Schneider Electr
17. IRENA (2021) Renewable power generation costs in 2020. International Renewable Energy Agency, Abu Dhabi
18. Energy Information Administration (EIA) (2021) Battery storage in the United States: an update on market trends
19. Mahieux C, Oudalov A (2016) Microgrids enter the mainstream. *Renew Energy Focus* 17(2):70–72. <https://doi.org/10.1016/j.ref.2016.02.010> [Crossref]
20. Laws ND, Anderson K, DiOrio NA, Li X, McLaren J (2018) Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings. *Renew Energy* 127:896–909. <https://doi.org/10.1016/j.renene.2018.05.011> [Crossref]
21. Schneider KP, Tuffner FK, Elizondo MA, Liu C-C, Xu Y, Ton D (2017) Evaluating the feasibility to use microgrids as a resiliency resource. *IEEE Trans Smart Grid* 8(2):687–696. <https://doi.org/10.1109/TSG.2015.2494867> [Crossref]
22. Ericson S, Anderson K, Engel-Cox J, Jayaswal H, Arent D (2018) Power couples: the synergy value of battery-generator hybrids. *Electr J* 31(1):51–56. <https://doi.org/10.1016/j.tej.2017.12.003>

- [Crossref]
23. Masrur H, Sharifi A, Islam MR, Hossain MA, Senjyu T (2021) Optimal and economic operation of microgrids to leverage resilience benefits during grid outages. *Int J Electr Power Energy Syst* 132:107137. <https://doi.org/10.1016/j.ijepes.2021.107137>
[Crossref]
 24. Marqusee J, Becker W, Ericson S (2021) Resilience and economics of microgrids with PV, battery storage, and networked diesel generators. *Adv Appl Energy* 3:100049. <https://doi.org/10.1016/j.adapen.2021.100049>
[Crossref]
 25. Rosales-Asensio E, de Simón-Martín M, Borge-Diez D, Blanes-Peiró JJ, Colmenar-Santos A (2019) Microgrids with energy storage systems as a means to increase power resilience: an application to office buildings. *Energy* 172:1005–1015. <https://doi.org/10.1016/j.energy.2019.02.043>
[Crossref]
 26. Anderson KH, DiOrio NA, Cutler DS, Butt RS (2017) Increasing resiliency through renewable energy microgrids. *Int J Energy Sect Manag* 2:69034
 27. Prudenzi A, Fioravanti A, Caracciolo V (2017) Resilient power in hospitals: the *S. giovanni addolorata* general hospital case study. In: *Proceedings of the 2017 AEIT international annual conference*, pp 1–6. <https://doi.org/10.23919/AEIT.2017.8240572>
 28. Masrur H, Senjyu T, Islam MR, Kouzani AZ, Mahmud MAP (2021) Resilience-oriented dispatch of microgrids considering grid interruptions. *IEEE Trans Appl Supercond* 31(8):1–5. <https://doi.org/10.1109/TASC.2021.3094423>
[Crossref]
 29. Lagrange A, de Simón-Martín M, González-Martínez A, Bracco S, Rosales-Asensio E (2020) Sustainable microgrids with energy storage as a means to increase power resilience in critical facilities: an application to a hospital. *Int J Electr Power Energy Syst* 119:105865. <https://doi.org/10.1016/j.ijepes.2020.105865>
[Crossref]
 30. Rosales-Asensio E, de Simón-Martín M, Rosales A-E, Colmenar-Santos A (2021) Solar-plus-storage benefits for end-users placed at radial and meshed grids: an economic and resiliency analysis. *Int J Electr Power Energy Syst* 128:106675. <https://doi.org/10.1016/j.ijepes.2020.106675>
[Crossref]
 31. Chino Valley Medical Center (2019) Fact sheet. <https://www.cvmc.com/about-us/fact-sheet/>

32. Anderson K et al (2021) REopt lite user manual. National Renewable Energy Lab.(NREL), Golden
33. Anderson KH et al (2017) REopt: a platform for energy system integration and optimization. National Renewable Energy Lab.(NREL), Golden
34. NREL (2018) REopt: renewable energy integration and optimization. <https://reopt.nrel.gov/tool>
35. OpenEI Basic information. <https://apps.openei.org/IURDB/rate/view/5571b25a5457a38e37db22a3>.
36. Southern California Edison Schedule TOU-8 Time-of-use: general service e large. <http://www.sce.com/NR/sc3/tm2/pdf/CE281.pdf>
37. Miguez CD (2018) Energy consumption in Spanish hospitals. Anuario AEIH, pp 37-40
38. Deru M et al (2011) US department of energy commercial reference building models of the national building stock. National Renewable Energy Laboratory, Golden
39. Klemeš JJ, Jiang P, Van Fan Y, Bokhari A, Wang X-C (2021) “COVID-19 pandemics stage II: energy and environmental impacts of vaccination. Renew Sustain Energy Rev 150:111400. <https://doi.org/10.1016/j.rser.2021.111400> [Crossref]
40. Küfeoğlu S, Lehtonen M (2015) Interruption costs of service sector electricity customers, a hybrid approach. Int J Electr Power Energy Syst 64:588-595. <https://doi.org/10.1016/j.ijepes.2014.07.046> [Crossref]
41. Anderson KH, Hotchkiss EL, Murphy C (2019) Valuing resilience in electricity systems. National Renewable Energy Lab.(NREL), Golden
42. Sullivan M, Schellenberg J, Blundell M (2015) Updated value of service reliability estimates for electric utility customers in the United States. Lawrence Berkeley National Lab.(LBNL), Berkeley
43. NREL (2020) 2020 Annual technology baseline and standard scenarios. Golden
44. U.S. Energy Information Administration (EIA) (2020) Annual energy outlook 2020. Washington DC
45. European Commission (2022) Photovoltaic geographical information system—PVGIS. https://re.jrc.ec.europa.eu/pvg_tools/en/. Accessed 01 April 2022

46. Dobos AP (2014) PVWatts version 5 manual. National Renewable Energy Lab.(NREL), Golden
47. NC Clean Energy Tech Center (2021) Database of state incentives for renewables and efficiency®. <https://programs.dsireusa.org/system/program/detail/658>
48. Mongird K et al (2019) Energy storage technology and cost characterization report. Pacific Northwest National Lab.(PNNL), Richland, WA
49. Mackenzie W (2019) U.S. energy storage monitor: Q3 2019 full report
50. DiOrio N, Dobos A, Janzou S (2015) Economic analysis case studies of battery energy storage with SAM. National Renewable Energy Lab.(NREL), Golden
51. Patsios C et al (2016) An integrated approach for the analysis and control of grid connected energy storage systems. J Energy Storage 5:48-61. <https://doi.org/10.1016/j.est.2015.11.011> [Crossref]
52. Anderson KH, Elggqvist EM, Settle DE (2018) Federal tax incentives for energy storage systems. National Renewable Energy Lab.(NREL), Golden
53. Lazard (2017) Lazard's levelized cost of energy analysis—Version 11.0
54. National Fire Protection Association (2019) NFPA 110: standard for emergency and standby power systems
55. Generator Source (2021) Approximate diesel fuel consumption chart. https://www.generatorsource.com/Diesel_Fuel_Consumption.aspx

Correction

Correction to: Energy Resilience: Definition and Assessment

Fellipe Sartori da Silva^{1, 2}  and José Alexandre Matelli¹ 

(1) Department of Chemistry and Energy, School of Engineering, São Paulo State University, Guaratinguetá, São Paulo, Brazil

(2) Department of Mechanical Engineering, Federal University of Paraná, Curitiba, Paraná, Brazil

 **Fellipe Sartori da Silva (Corresponding author)**
Email: fellipe.sartori@ufpr.br

 **José Alexandre Matelli**
Email: jose.a.matelli@unesp.br

The updated version of this chapter can be found at https://doi.org/10.1007/978-3-031-67754-0_1

Correction to: Chapter “Energy Resilience: Definition and Assessment” in: D. Borge-Diez and E. Rosales-Asensio (eds.), *Energy System Resilience and Distributed Generation, Power Systems*, https://doi.org/10.1007/978-3-031-67754-0_1

In the original version of the book, the author's name “Sartori da Silva Fellipe” has been changed to read as “Fellipe Sartori da Silva” in Chapter 1. The book and the chapter have been updated with the change.